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IFTA Journal 18

Inside this Issue

"Throw off the bowlines, sail away from the safe harbour. Explore. Dream. Discover."

—Mark Twain

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The attention to its customers' ongoing financial training has always been a key factor in Webank's market approach, strategy and customer care. As a matter of fact, since 2010, more than 600 Webank events and webinars have focused on a gamut of financial topics with the active participation of highly qualified and famous speakers and professional traders.

IFTA Journal

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Certified Financial Technician (CFTe) Program

IFTA Certified Financial Technician

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

Master of Financial Technical Analysis (MFTA) Program

IFTA Master of Financial Technical Analysis

IFTA's Master of Financial Technical Analysis (MFTA) represents the highest professional achievement in the technical analysis community, worldwide. Achieving this level of certification requires you to submit an original body of research in the discipline of international technical analysis, which should be of practical application.

Examinations

In order to complete the MFTA and receive your Diploma, you must write a research paper of no less than three thousand, and no more than five thousand, words. Charts, Figures and Tables may be presented in addition.

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

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

Please visit our website at http://www.ifta.org/certifications/master-of-financial-technical-analysis-mfta-program/ for further details and to register.

Cost

$950 US (IFTA Member Colleagues);
$1,200 US (Non-Members)

International Federation of Technical Analysts

Letter From the Editor

By Aurélia Gerber, MBA, CFA, MFTA

Dear IFTA Colleagues and Friends:

The *IFTA Journal*, along with this year's 30th conference in Milan under the theme "Sailing to the Future", will allow us to go beyond the usual thematic of technical analysis, exploring the sea of opportunities that has been originated by a totally new "quant" generation of technologies, markets, and instruments.

Technical analysis is the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends. The three principal sources of information available to the technician are price, volume, and open interest. The premises of technical analysis remain the same, however: price discounts everything; price movements are not totally random—they move in trends; and history has a tendency to repeat itself.

Since the principles of technical analysis are universal, it is easy to broaden the focus to all financial markets fostering a common language for traders and investors.

The *IFTA Journal* is—through its global distribution to professionals in the field within member societies from 27 countries—one of the most important forums for publishing leading work in technical analysis. The variety of content provides unique opportunities for readers to advance their knowledge and understanding of the practice of technical analysis.

"Technical analysis is the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends."

The *IFTA Journal* is divided into several sections:

In the first section, we have published four Master of Financial Technical Analysis (MFTA) research submissions. This section offers fresh ways of looking at the behavior of markets and is testament to the high standing of the MFTA designation.

The first paper deals with neural network and ensemble learning to improve trading performance. The second paper is on systematic trading strategies based on K divergence, the third introduces a new technical tool—the M-oscillator—and the fourth paper proves higher systematic risk-adjusted returns using technical indictors.

The second section includes articles submitted by IFTA colleagues: one article was submitted by an Egyptian Society of Technical Analysis (ESTA) member on time cycle oscillators, and three articles were submitted by Vereinigung Technischer Analysten Deutschlands (VTAD). The first VTAD award introduces the Key Performance Indicator (KPI), the second VTAD award deals with the question of empirical evidence of magic cycles in stocks and index charts, and the third VTAD award investigates the combination of several trading signals and social trading.

Next, for the sixth year, we are happy to publish a paper from another organisation, and with the permission of the National Association of Active Investment Managers (NAAIM), we have included a paper by Franklin J. Parker, winner of the 2017 NAAIM Founders Award. We hope that you find this paper most interesting. We are also very thankful to have had the support of our book reviewer, Regina Meani, CFTe, on *The Handbook of Technical Analysis*, by Mark Andrew Lim.

This year's *Journal* was produced by a returning team for IFTA. I would like to thank Elaine Knuth, CFTe, and Rolf Wetzer for their help in editing this *Journal*.

We are also able to create this timely and unique *Journal* because of the intellect and generosity of time and materials from the authors. It was their tremendous spirit and endeavour that enabled us to achieve the goals of this high quality journal. We are indebted to all authors for their contributions and for enabling us to meet our *Journal* submission deadline.

We would also like to thank the production team at Management Solutions Plus, in particular, Linda Bernetich and Lynne Agoston, for their administrative, technical, editorial and publishing work.

Last but not least we would like to pay tribute to our dear IFTA colleague and friend Hank Pruden, who passed away on 26th September. Hank has been an active contributor to IFTA in many ways—writing articles for both the *Journal* and the newsletter as well as presenting at IFTA conferences. He was passionate about teaching and sharing his knowledge with others. We will miss the brilliant technician, educator, and visionary as well as the wonderful human being. We have lost one of our brightest stars.

Consensus Ratio and Two-Step Selection to Detect Profitable Stocks

By Tomoyo Suzuki, Ph.D., CMTA, MFTA, CFTe

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Abstract

Along with the development of computer technology, the machine learning approach has been used for investment purposes. Since it basically uses only historical price movements to predict future behavior, it can be considered as a technical analysis and is especially called modern technical analysis. Moreover, the ensemble learning algorithm is also used as a computational technique to improve the prediction accuracy by reproducing many independent predictors from a machine learning method and averaging these predictors. However, there was no technique to focus on the variance of them, which shows the degree of consensus; smaller variance means higher consensus and more confident prediction. For this viewpoint, the present study calls it "the consensus ratio" and demonstrated how to apply it as a technical indicator. However, as a problem, when we apply the consensus ratio to unpredictable stocks, it sometimes happens to show high consensus. To prevent this problem, the first selection removes the stocks whose prediction accuracies were worse in the back test. Then, the second selection salvages profitable stocks whose consensus ratios are higher. To confirm the profitability of my framework, I performed investment simulations using the real data of 590 stocks listed in the Tokyo Stock Exchange (TSE) and 500 stocks listed in the New York Stock Exchange (NYSE). In addition, to confirm the validity of the stocks selected by my two-step selection, I also performed the statistical significance test comparing the original strategy to its randomized strategies. Through these simulations, I could obtain positive results, which could be considered counterevidence to the efficient market hypothesis.

Introduction

Recently, the neural network has been spotlighted again because of some breakthroughs in the field of artificial intelligence; for example, Google's AlphaGo, which is a computer program based on the deep neural networks,[1] beat the human champion of Go in 2016. This machine-based approach can be also used for predicting time-series data, like stock price movements. On the other hand, humans have limitations in recognizing complex patterns hidden in time-series data, and therefore, humans want to ask computers to detect complex patterns automatically. The neural network is one of the machine-based learning algorithms for nonlinear prediction. However, it is the same as traditional technical analyses in terms of using only past historical data for prediction, and so it is occasionally called "modern technical analysis." From this viewpoint, the present thesis discusses more advanced modern technical analyses. In particular, I also apply the ensemble learning method[2] to enhance the predictive power of the neural network and compose a new technical indicator to evaluate the confidence of each prediction. Moreover, to select the most confident stock adaptively, I introduce how to use my technical indicator. Finally, to confirm the profitability of my framework, I perform investment simulations using real stock data during the four terms in the Japanese market and the American market.

Nonlinear Prediction Model

The linear regression analysis is well-known as the most basic prediction model. We can easily examine what factors affect future movements by this model, but it has limitations in expressing the relationship between past and future movements because there is the assumption that this relationship is linear. However, real financial markets must be more complex, and therefore it would be better to use nonlinear prediction models. For this reason, the present thesis uses the neural network model for nonlinear prediction.

Neural Network Model

First of all, any prediction models can be simply described as follows:

$$\text{Future} = F(\text{Past})$$

where *"F"* means the relationship between past and future movements. If the function *F* gets "Past" data as inputs, then "Future" can be predicted as an output from the function *F*. For example, the linear regression can be expressed as follows:

$$\begin{aligned}\hat{x}(t+1) &= F(\,x(t), x(t-1), \cdots, x(t-d)\,)\\ &= w_0x(t) + w_1x(t-1) + \cdots + w_dx(t-d)\end{aligned}$$

where $w_0, w_1, \cdots, w_d$ are regression coefficients and $\hat{x}$ is a predicted value. In this thesis, x means a return rate. Namely,

$$x(t) = \frac{price(t) - price(t-1)}{price(t-1)}$$

Next, to modify the regression into a nonlinear version, the sigmoid function $f(x) = \frac{1}{1+\exp(-x)}$ is inserted as a nonlinear filter f shown below.

$$\begin{aligned}\hat{x}(t+1) &= F(\,x(t), x(t-1), \cdots, x(t-d)\,)\\ &= f(\,w_0x(t) + w_1x(t-1) + \cdots + w_dx(t-d)\,)\\ &= \frac{1}{1+\exp[-(\,w_0x(t) + w_1x(t-1) + \cdots + w_dx(t-d)\,)\,]}\end{aligned}$$

This is called the single neuron model, whose diagram is shown in Figure 1. Although this neuron model is a nonlinear prediction model, its nonlinearity is not high and the outputted return rate $\hat{x}(t+1)$ is only positive value like $\hat{x}(t+1) \in [0,1]$. Of course, we can modify $\hat{x}(t+1)$ into $2 \cdot \hat{x}(t+1) - 1 \in [-1,1]$. However, we can also mix many single neurons as shown in Figure 2 in order to compose a more complex nonlinear function F. This is a neural network, which can be denoted as follows:

$$\hat{x}(t+1) = F(\, x(t), x(t-1), \cdots, x(t-d)\,)$$
$$= w_1 o_1 + w_2 o_2 + \cdots + w_j o_j + \cdots + w_N o_N$$
$$o_j = \frac{1}{1 + \exp[-(\, w_{0,j} x(t) + w_{1,j} x(t-1) + \cdots + w_{d,j} x(t-d)\,)]}$$

where $\{w_1, w_2, \cdots, w_N\}$ and $\{w_{0,j}, w_{1,j}, \cdots, w_{d,j} \mid j = 1 \sim N\}$ are model parameters, d is the number of the first layer neurons, N is the number of the second layer neurons, and o_j is an output value from the j-th neuron on the second layer. Here, because $w \in [-\infty, \infty],\ \hat{x}(t+1) \in [-\infty, \infty]$.

Figure 1. The single neuron model

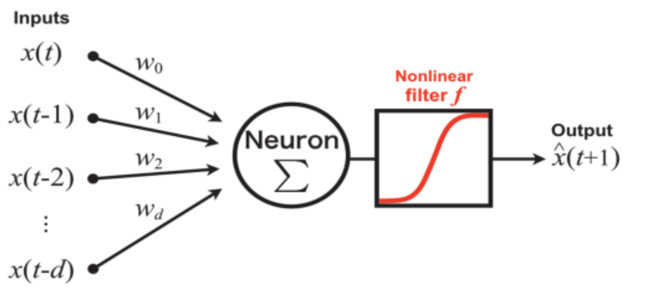
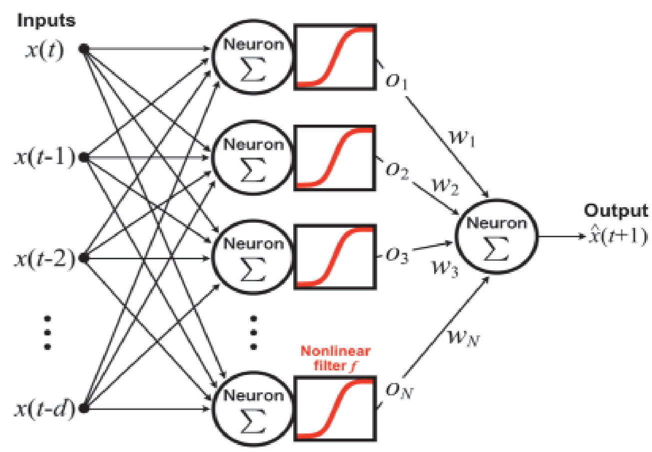


Figure 2. The neural network model



Optimization to Prevent Overfitting

Before performing prediction, we have to train a neural network, that is, optimize all of the model parameters w so as to accurately reproduce the previous output data from the input data. Because the training algorithms are mathematically complex, let me mention only their results. The parameters of $\{w_1, w_2, \cdots, 2_N\}$ are modified by the steepest descent method[2]:

$$w_j \leftarrow w_j + \eta(x^*(t+1) - \hat{x}(t+1))o_j(t)$$

where, $j \in \{1, \cdots, N\}$, $\hat{x}(t+1)$ is a predicted output data, and $x^*(t+1)$ is its answer (so-called teacher signal). Then, η is the training coefficient and is set to 0~1. Next, if the number of the third layer neuron is one like Figure 2, $\{w_{0,j}, w_{1,j}, \cdots, w_{d,j} \mid j = 1 \sim N\}$ are modified by the back-propagation algorithm:[2]

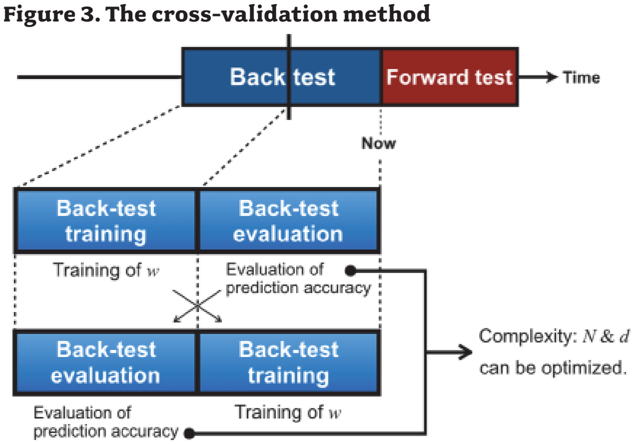
$$w_{i,j} \leftarrow w_{i,j} + \eta w_j\big(x^*(t+1) - \hat{x}(t+1)\big)x(t-i+1)$$

where $i \in \{1, \cdots, d\}$. Until the total of training errors between $x^*(t+1)$ and $\hat{x}(t+1)$ of the historical data set becomes small enough, the above modifications are repeated. If this training process is called "Back test" as shown in Figure 3, the total of training errors can be evaluated by the mean squared error E:

$$E = \frac{1}{\beta} \sum_{t=\alpha}^{\alpha+\beta-1} \big(x^*(t+1) - \hat{x}(t+1)\big)^2$$

where α is the starting time of the back test and β is the total length of the test.

Figure 3. The cross-validation method



After training all the parameters, we can use the neural network to predict new data. If the trained neural network is denoted as $\hat{F}$, we can get the predicted value $\hat{x}(t+1)$ by

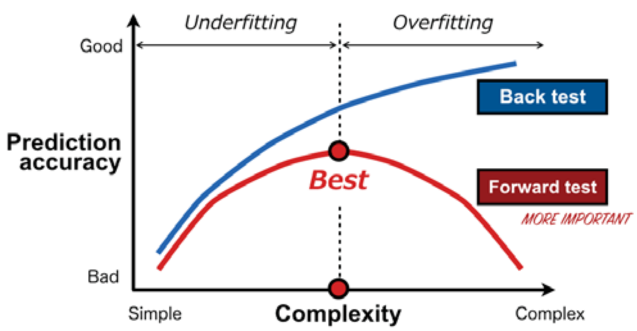
$$\hat{x}(t+1) = \hat{F}(\, x(t), x(t-1), \cdots, x(t-d)\,)$$

where $\{x(t), x(t-1), \cdots, x(t-d)\}$ are new return rates. Here, let me call this prediction "Forward test" in Figure 3.

However, in the back test to train model parameters, we have to take care of the overfitting (curvefitting) problem. It is meaningless if the trained neural network works well only in the back test. Of course, the forward test is more important for evaluating prediction models. As shown in Figure 4, this problem depends on the complexity of the prediction model. As a prediction model becomes more complex, it can learn everything, even noise, and overfit into the training data through the back test. Therefore, the prediction accuracy during the back test becomes better, but it becomes worse during the forward test because the overfitted prediction model cannot work for new untrained data. To prevent this overfitting, we have to select the best complexity for a neural network whose complexity corresponds to the number of neurons N and that of input data d. Therefore, it is also important how to determine these numbers in the back test.

However, before the forward test, we cannot evaluate how bad the trained neural network was overfitted to the training data. To solve this problem, the cross-validation method is often used in the field of machine learning[2] to find the best complexity during the back test. As shown in Figure 3, the training data set that we have already obtained is first separated into two parts for the back-test training and for the back-test evaluation. Next, a neural network can be trained through the back-test training to optimize the model parameters w and then evaluate its predictive power (i.e., the mean squared error E) through the back-test evaluation. After that, we change these two parts and do the same thing. Finally, so as to minimize the mean squared error E given by two evaluation parts, we can find the best complexity of neural network (i.e., N and d).

Figure 4. The best complexity between underfitting and overfitting (The back test optimizes the connection strength *w* between neurons, and the forward test evaluates the optimized neural network in terms of overfitting.)



Forward Test of Prediction Accuracy

After the cross-validation method, let me confirm the predictive power of the trained and optimized neural network. Namely, I perform forward tests using new untrained data. In this thesis, I used 590 stocks listed in the Tokyo Stock Exchange (TSE) and 500 stocks listed in the New York Stock Exchange (NYSE), and these stock prices were observed in four different terms. Namely, it means that over 4,000 stocks were simulated in total. Then, all stock data are daily opening prices. The detail is shown in Table 1. In this forward test, I apply the neural network trained by the back test, which supposes that a term composed by both back test and forward test maintains the same market tendency. Therefore, to evaluate the tendency of each term, the rate of advancing stocks (e.g., bullish or bearish) was calculated by including both periods of the back test and forward test. As a result, each term has different properties in terms of market trends. Then, because I wanted to use a completely different data set to compose neural networks, the period of each back test was shifted to make four terms without any overlaps or blanks.

Table 1. The detail of real stock price data used for simulations*

Market		Tokyo stock exchange	New York stock exchange
Data source		Yahoo! finance Japan[3]	Yahoo! finance[4]
# of stocks		590	500
First term	Back test (for the cross-validation method)	1991/1 ~ 1995/12 (5 years) (Training: 2.5 years, evaluation: 2.5 years)	
	Forward test (for investment period)	1996/1 ~ 1998/6 (2.5 years)	
	Rate of advancing stocks (during all the term)	14.9% (Strong bearish)	69.3% (Bullish)
Second term	Back test (for the cross-validation method)	1996/1 ~ 2000/12 (5 years) (Training: 2.5 years, evaluation: 2.5 years)	
	Forward test (for investment period)	2001/1 ~ 2003/6 (2.5 years)	
	Rate of advancing stocks (during all the term)	55.9% (Bullish)	60.5% (Bullish)
Third term	Back test (for the cross-validation method)	2001/1 ~ 2005/12 (5 years) (Training: 2.5 years, evaluation: 2.5 years)	
	Forward test (for investment period)	2006/1 ~ 2008/6 (2.5 years)	
	Rate of advancing stocks (during all the term)	17.1% (Bearish)	59.1% (Bullish)
Fourth term	Back test (for the cross-validation method)	2006/1 ~ 2010/12 (5 years) (Training: 2.5 years, evaluation: 2.5 years)	
	Forward test (for investment period)	2011/1 ~ 2013/6 (2.5 years)	
	Rate of advancing stocks (during all the term)	69.2% (Bullish)	82.2% (Strong bullish)

*I used only the stocks that have no missing data in all terms. Of course, this screening was performed before any simulations, such as training neural networks, and therefore, there is no worry about the survivorship bias. Then, the data length of training period of each stock is roughly 1,250 because a year includes about 250 business days.

Table 2 shows the prediction accuracy during the forward test in each term. Each prediction accuracy is the average value of the same market and same term. Then, in this thesis, I try to predict whether the next stock price will go up (i.e., the return rate $x(t+1) \geq 0$) or down (i.e., $x(t+1) < 0$). Therefore, the accuracy rate of this alternative question stands for the prediction accuracy, and over 50% means a good prediction. Besides, for the cross-validation method introduced in Section 2.2, this accuracy rate was used as the prediction accuracy instead of the mean squared error E. Namely, the complexity of neural networks was optimized by maximizing this accuracy rate, not by minimizing E, in the back-test evaluation. Then, the prediction accuracy shown in Table 2 was not given by the back-test evaluation, but by the forward test. As a result, we can see that every case realized over 50%, which means that real return rates are a little predictable. However, each prediction accuracy is not high.

Table 2. Average of prediction accuracy during the forward test

	Tokyo stock exchange	New York stock exchange
First term	54.8%	59.1%
Second term	55.8%	52.7%
Third term	51.6%	52.0%
Fourth term	54.8%	53.2%

Ensemble Learning Method

To improve prediction accuracy, let me use the ensemble learning method. This is the second technique in my framework.

Example of Ensemble Learning

First, let me show an example to confirm the power of ensemble learning. Please consider this question: will tomorrow's stock price go up or down? This is an alternative question. In addition, please imagine this situation: you have 19 kinds of prediction methods, and each prediction accuracy is only 53% similar to the neural network shown in Table 2. Namely, each prediction accuracy is not high. In this situation, what percentage of questions can you answer correctly by following their majority decision? Here, the majority decision is the consensus of more than 10 predictors because you have 19 predictors.

This percentage can be calculated by the probability theory. If each prediction method is independent, the probability that x out of 19 predictors answer correctly obeys the binomial distribution:

$$P(x) = {}_{19}C_x p^x (1-p)^{19-x}$$

where $p = 0.53$. Then, the probability that this majority decision is correct can be calculated by integrating the cases that x is more than 10:

$$\sum_{x=10}^{19} P(x) = 0.60$$

Thus, the prediction accuracy has been improved from 53[%] to 60[%] by taking the majority decision. This is an effect of the ensemble learning.

Table 3 shows other cases in which the initial prediction accuracy p of each prediction method is different. Of course, if $p = 50\%$ (i.e., unpredictable), its prediction accuracy cannot be improved even by the ensemble learning. However, if $p > 50\%$, it can be improved very much. For this reason, I apply this ensemble learning to the neural network model.

Table 3. Prediction accuracy improved by the majority decision based on 19 predictors

Initial prediction accuracy	50%	55%	60%	65%	70%
Prediction accuracy of the majority decision	50%	**67%**	**81%**	**91%**	**97%**

Ensemble Learning for Neural Network

As mentioned above, to improve the prediction accuracy, the ensemble learning requires an essential condition that each prediction method should be independent. Although this condition cannot be perfectly satisfied, the bagging algorithm[5] is often used in the field of machine learning to approximately satisfy the condition.

To independently train many neural networks, first, all of the training data are randomly resampled with replacement, but the relationship between each set of inputs and its ideal output (i.e., the teacher signal x^*) must be kept, as shown in Figure 5. Then, by repeating it many times, different training data sets are independently made and can be applied to independently train neural networks, as shown in Figure 6. After the training, we can use all of them to obtain many predicted values in the forward test. Finally, the most frequent answer can be found from them as the majority decision, and it is the final answer given by ensemble learning.

Table 4 shows the prediction accuracy of the ensemble neural networks, where I used the same stock data as Table 2 and independently trained 1,000 different neural networks for the ensemble learning. As you can see, all of the cases were improved up to about 60%, but still these are not high enough.

Figure 5. An example of randomized training data for ensemble learning (In practice, the number of training data is more than 10.)

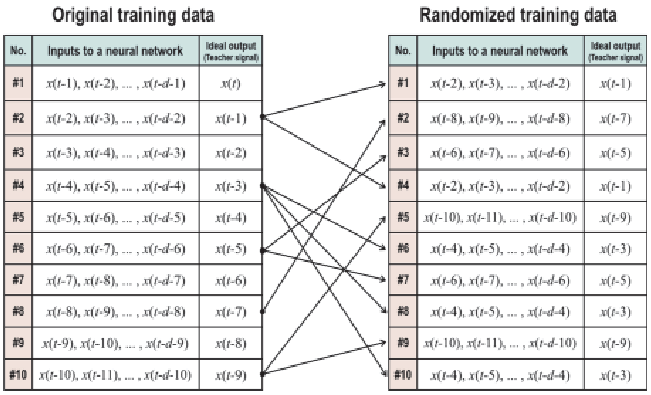


Figure 6. Ensemble learning with neural networks (First, neural networks are trained by resampled data sets, and secondly, they are applied to predict new data for the forward test by following the majority decision.)

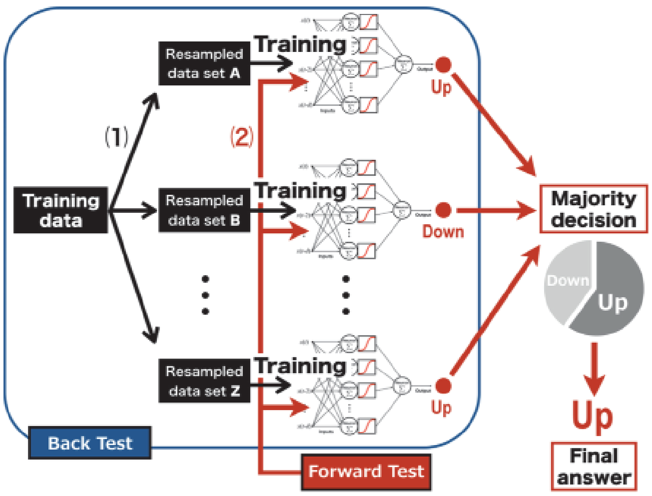


Table 4. Average of prediction accuracy improved by ensemble learning (Each prediction accuracy was calculated by the forward test.)

	Tokyo stock exchange	New York stock exchange
First term	59.9%	61.7%
Second term	57.9%	55.6%
Third term	55.5%	55.3%
Fourth term	57.0%	54.6%

Consensus Ratio

To improve the prediction accuracy, let me propose a new technical indicator as the third technique in my framework. Although ensemble learning normally focuses on the average or the most frequent answer in an ensemble of predicted values, my previous study[6] focused on the variance of an ensemble to estimate the prediction risk. If the variance is large, it means that prediction methods composing an ensemble set output different answers. Therefore, this ensemble learning is risky because the consensus of prediction methods is low.

From this viewpoint, I propose a technical indicator that is called the consensus ratio C:

$$C(\hat{x}(t+1) \geq 0) = \frac{\text{The number of } \hat{x}(t+1) \geq 0 \text{ in an ensemble}}{\text{The total number of predicted answers in an ensemble}}$$

which shows how many prediction methods answered $\hat{x}\,(t+1) \geq 0$ in an ensemble. Namely, as C is larger, the predicted answer is more reliable and confident. Then, this consensus ratio is used for each stock separately, and a threshold Θ is set to decide whether we can believe the final answer given by ensemble learning or should ignore it. In this thesis, I set $\Theta = 50\%$. Therefore, when $C(\hat{x}\,(t+1) \geq 0) < 50\%$, I did not use its predicted stock at the time t.

Two-Step Stock Selection

There is a concern about the consensus ratio, however. If it is applied to unpredictable stocks, it sometimes happens to show high consensus. To prevent this problem, the first selection is a kind of filter to remove the unpredictable stocks whose prediction accuracies were worse in the back-test evaluation. In this thesis, the first selection removes 75% stocks in the end of the back test and passes only the top 25% stocks to the second selection that will be performed along with the forward test. This concept is shown in Figure 7.

Next, the consensus ratio C is used in the forward test. However, even in predictable stocks, their consensus ratios fluctuate very much. For this reason, the second selection adaptively detects the most reliable stock that shows the largest consensus ratio each day. Therefore, the second selection is performed along with the forward test.

Table 5 shows the prediction accuracy of the two-step stock selection, where I used the same stock data set as Table 2 and Table 4, but the selected stock was changed every day in the forward test because it was adaptively determined by the second selection. Of course, because the two-step stock selection, even the second selection, used only the already known stock prices until the present time t, the given results must not have any unfair bias for calculating the prediction accuracies shown in Table 5. As a result, all of the cases were improved up to about 70%. I think that these accuracies are high enough for the prediction of real stock price movements.

Figure 7. Diagram of two-step stock selection

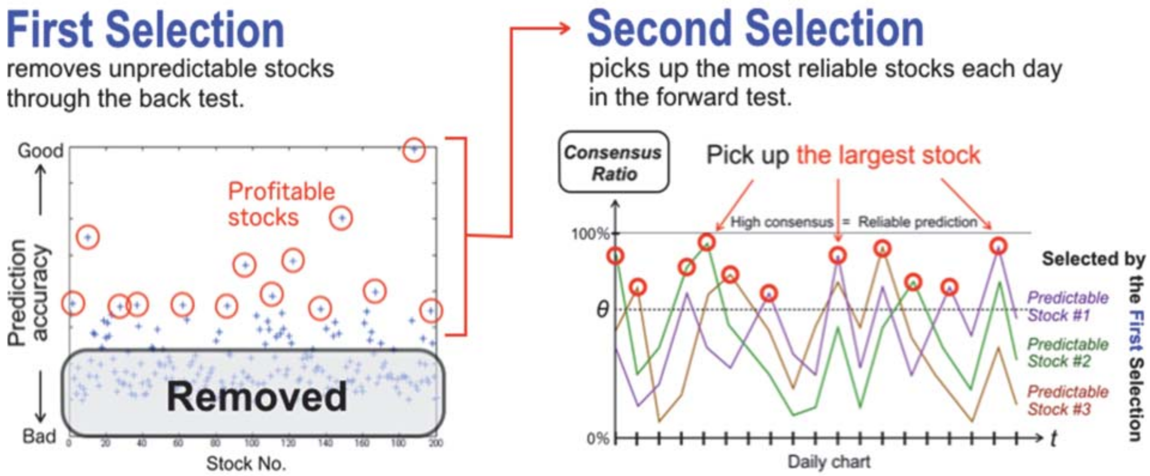


Table 5. Prediction accuracy improved by the two-step adaptive stock selection (Each prediction accuracy was calculated by the forward test.)

	Tokyo stock exchange	New York stock exchange
First term	65.9%	84.0%
Second term	71.6%	69.0%
Third term	60.4%	60.5%
Fourth term	62.1%	57.0%

INVESTMENT SIMULATIONS

Finally, I confirm the profitability of my framework composed by three techniques: the neural network, its ensemble learning, and the two-step stock selection based on the consensus ratio.

Performance of My Proposed Method

My investment strategy is very simple because I want to examine the relationship between the predictability shown in Table 5 and its profitability. Therefore, I bought the stock that was adaptively selected each day and sold it the next day. The selected stock showed the largest consensus ratio of $C(\hat{x}(t+1) \geq 0)$ which means that this stock would go up next day, and so I bought it at time t and sold it at time $t+1$. Here, buy and sell are executed at the opening of the market.

In addition, I assume that I observe new opening prices of all stocks every morning and immediately predict $\hat{x}(t+1)$ of them by the ensemble neural networks. Just after that, I calculate $C(\hat{x}(t+1) \geq 0)$ of them, and invest the stock that shows the largest consensus ratio. However, if the largest consensus ratio is smaller than Θ, the day does not perform any investment. As a supplement, if you want to also take short positions, the opposite version of the consensus ratio:

$$C(\hat{x}(t+1) < 0) = \frac{\text{The number of } \hat{x}(t+1) < 0 \text{ in an ensemble}}{\text{The total number of predicted answers in an ensemble}}$$

is useful, but the present thesis does not use it for simplicity.

Next, the temporal behavior of asset is calculated by

$$M_1(t) = M_1(1) + M_1(1) \cdot x(1) + \cdots + M_1(1) \cdot x(t) = M_1(t-1) + M_1(1) \cdot x(t)$$

$$M_2(t) = M_1(1) \cdot (1 + x(1)) \cdot (1 + x(2)) \cdot \cdots \cdot (1 + x(t)) = M_2(t-1) + M_2(t-1) \cdot x(t)$$

where the initial assets $M_1(1)$ and $M_2(1)$ are considered one. Therefore, $M_1(t)$ and $M_2(t)$ correspond to asset growth rates, but $M_1(t)$ is the additive growth rate based on the simple interest and $M_2(t)$ is the multiplicative growth rate based on the compound interest. Then, $x(t)$ is the realized return rate of the stock bought at time t-1 and sold at time t. If there is no investment at time t-1, then $x(t) = 0$. Here, if the commission cost $cost(t)$ is required for buying and selling stocks,

$$x(t) = \frac{price(t) - price(t-1) - cost(t)}{price(t-1)}$$

$$cost(t) = \frac{c}{100} \cdot (price(t) + price(t-1))$$

where c is the commission rate [%]. Nowadays, there are lots of online brokers whose commission rates c are under 0.1[%]. In particular, there is also the case of c=0[%], such as the margin transaction of SMBC Nikko Securities Inc.

For comparison with my proposed method, I also calculate the market average based on the buy-and-hold strategy, as follows:

$$M_3(t) = M_3(t-1) + M_3(t-1) \cdot \bar{x}(t)$$

where similarly $M_3(1) = 1$ and $\hat{x}(t)$ is the average of return rates of all stocks at time t. Because of the buy-and-hold strategy, its asset growth rate is calculated by the multiplicative type and the commission cost is not required.

Figures 8 and 9 show the temporal change of the additive asset growth rate $M_1(t)$ during the forward test, where I used the same stock data shown in Table 1, but the invested stock was changed every day because it was adaptively determined by the second selection. As a result, in all terms and markets, my framework shown as "Two-step selection" worked well and realized better performance than the market average $M_3(t)$. Moreover, Figures 12 and 13 show the temporal change of the multiplicative asset growth rate . Naturally, we can confirm that the compound interest could enhance the asset growth rate more than the simple interest.

Next, to simulate more realistic cases, I set the commission rate as c=0.1[%]. As mentioned above, c=0.1[%] or less is a common value in online brokers. The results are shown in Figures 10 and 11 for the additive growth rate and in Figures 14 and 15 for the multiplicative growth rate . The Japanese market still shows that my proposed method was better than the market average in all four terms, but the American market shows that my proposed method was almost the same as the market average in the third and fourth terms. Furthermore, if c=0.2[%] in the Japanese market, the advantage of my proposed two-step selection was lost in the third and fourth terms. However, if we use ordinary online brokers (c=0.1[%]), my proposed method might be profitable. To investigate this profitability in more detail, I will perform some statistical significance tests in the next section.

Figure 8. Temporal change of the additive asset growth rate $M_1(t)$ during the forward test in the Japanese market with the commission rate c=0[%] (Please see the text about the randomized strategies and p-value [%]. For comparison, the market average was calculated by $M_3(t)$ in this section.)

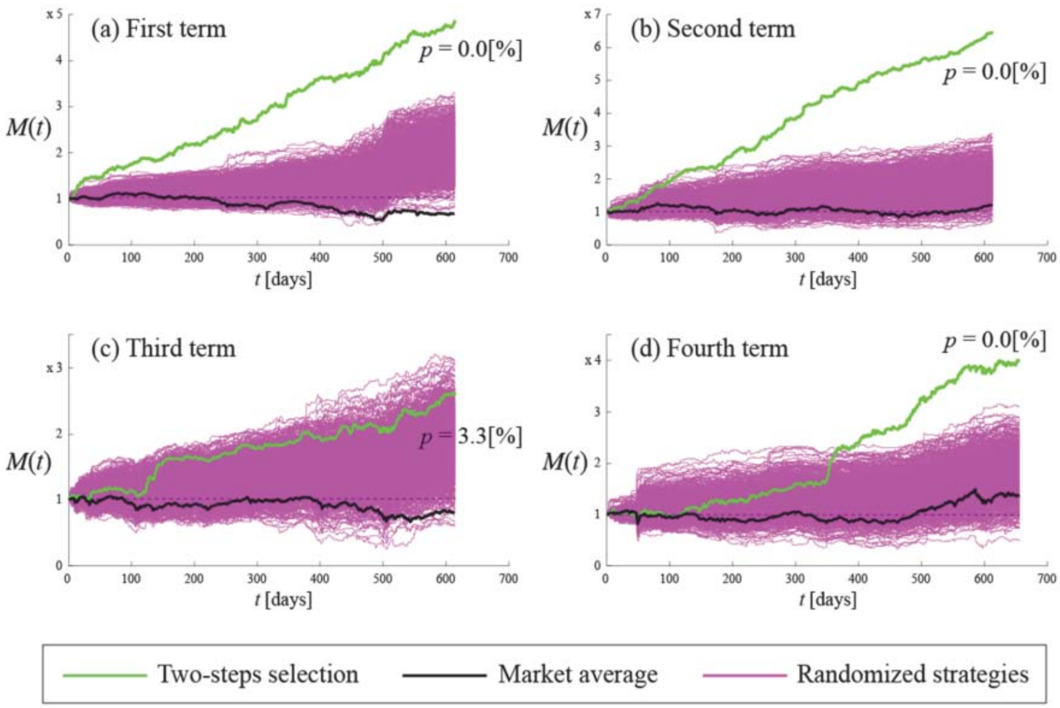


Figure 9. The same as Figure 8, but in the American market (c=0[%])

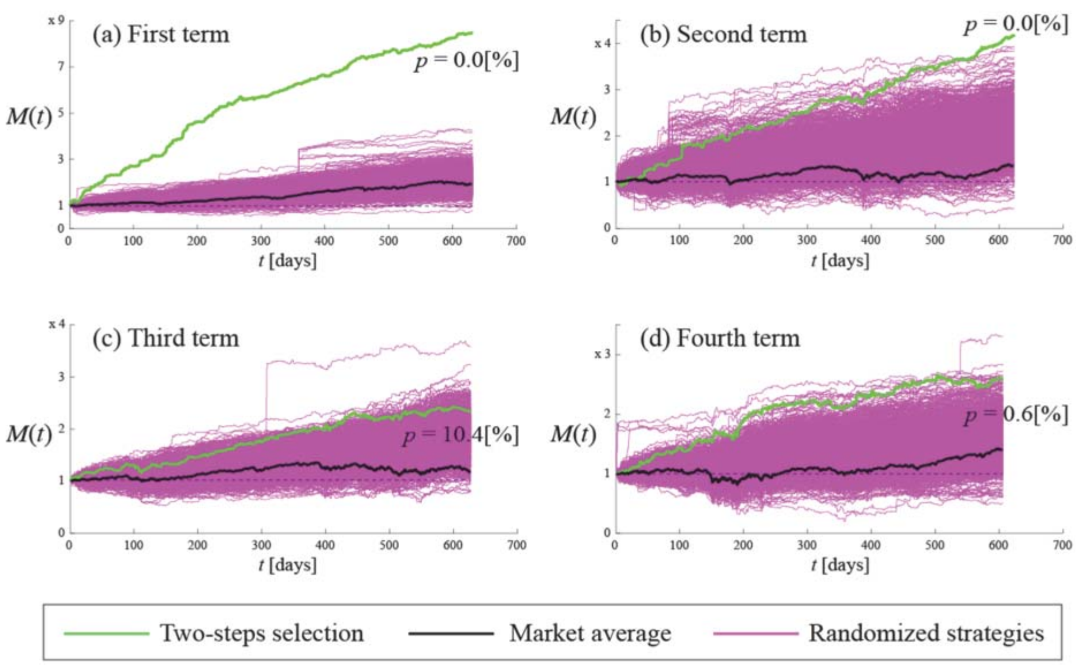


Figure 10. The same as Figure 8, but in the Japanese market (*c*=0.1[%])

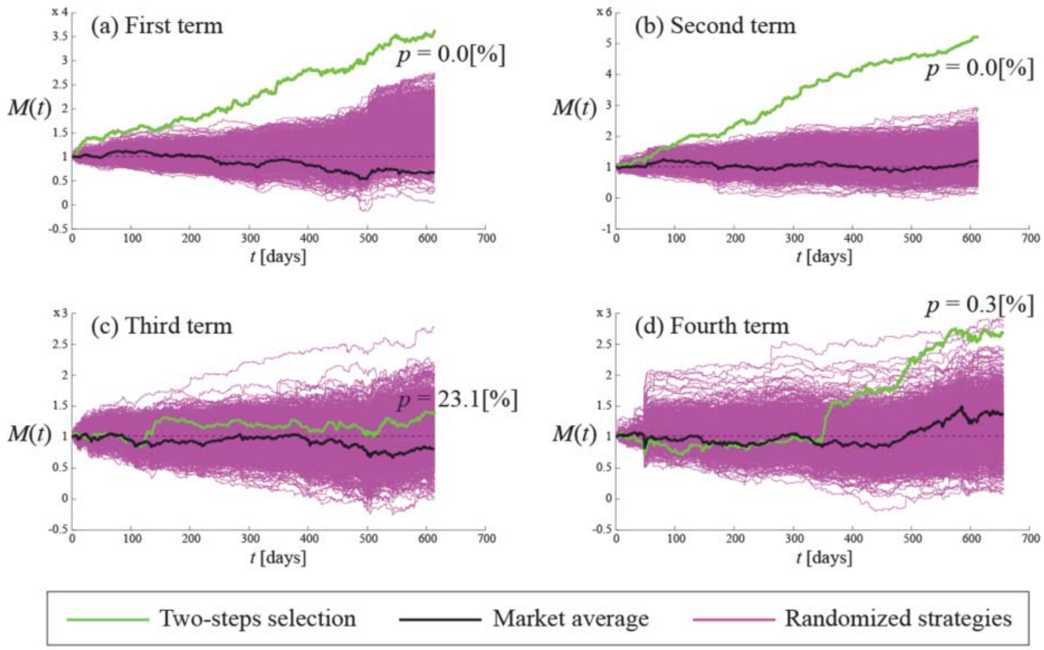


Figure 11. The same as Figure 8, but in the American market (*c*=0.1[%])

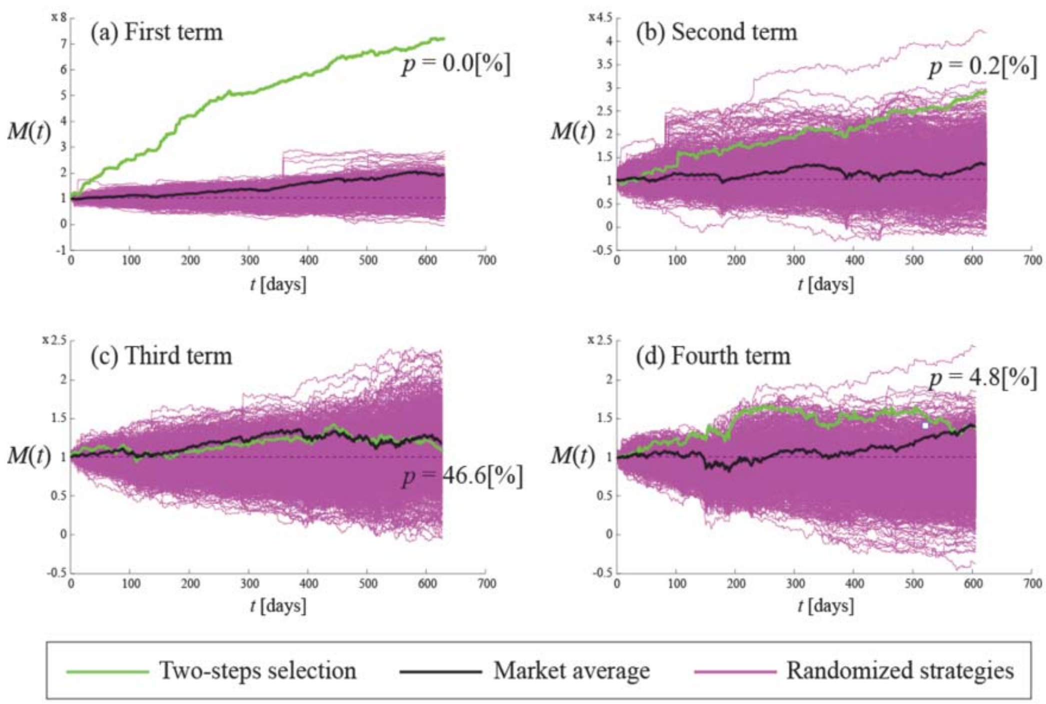


Figure 12. Temporal change of the multiplicative asset growth rate $M_2(t)$ during the forward test in the Japanese market with the commission rate c=0[%] (Please see the text about the randomized strategies and p-value [%]. For comparison, the market average was calculated by $M_3(t)$ in this section.)

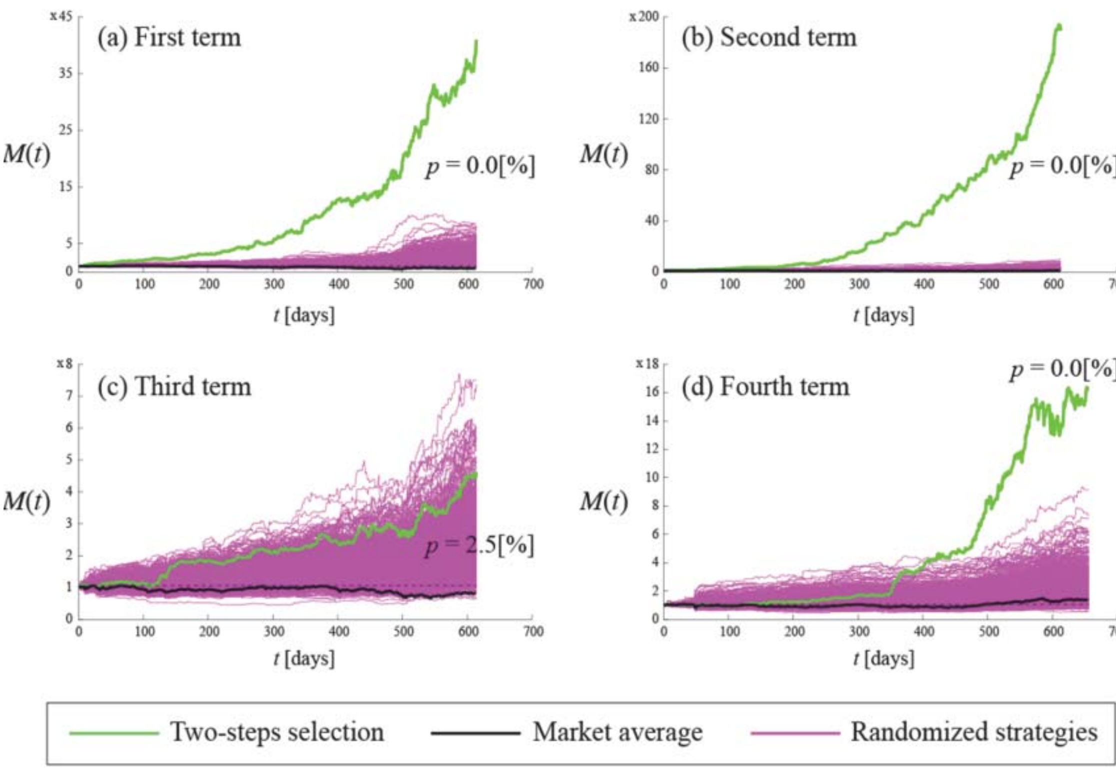


Figure 13. The same as Figure 12, but in the American market (c=0[%])

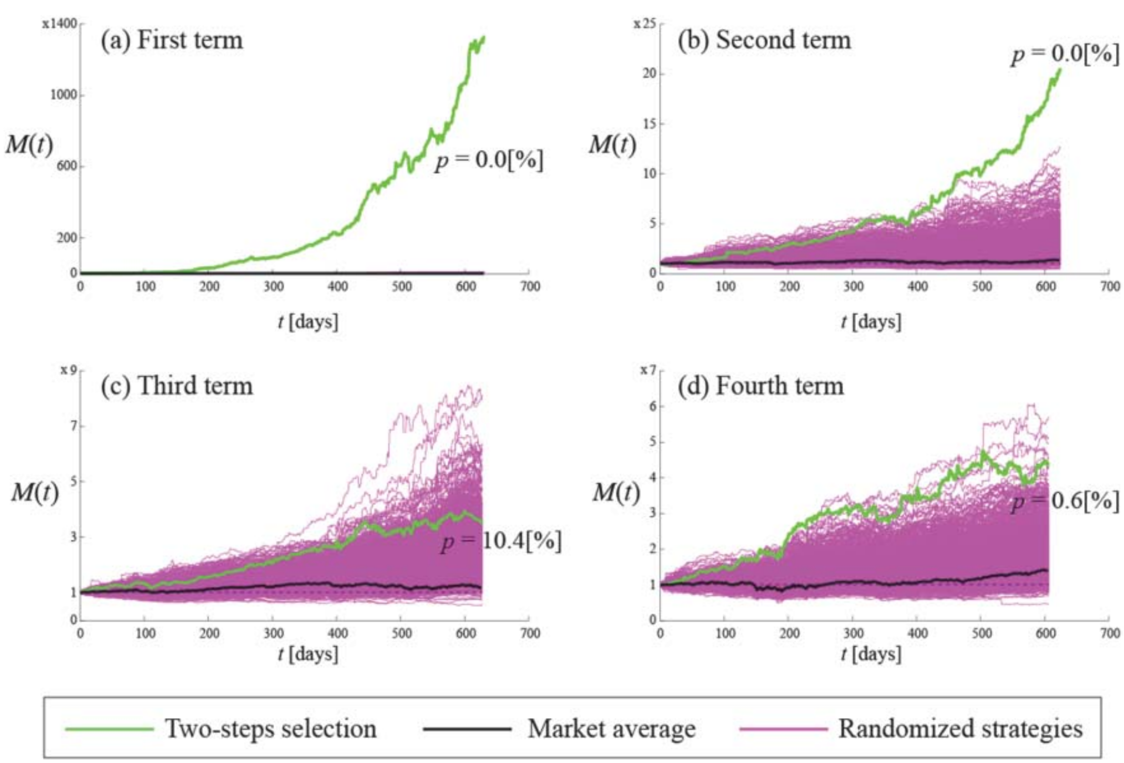


Figure 14. The same as Figure 12, but in the Japanese market (c=0.1[%])

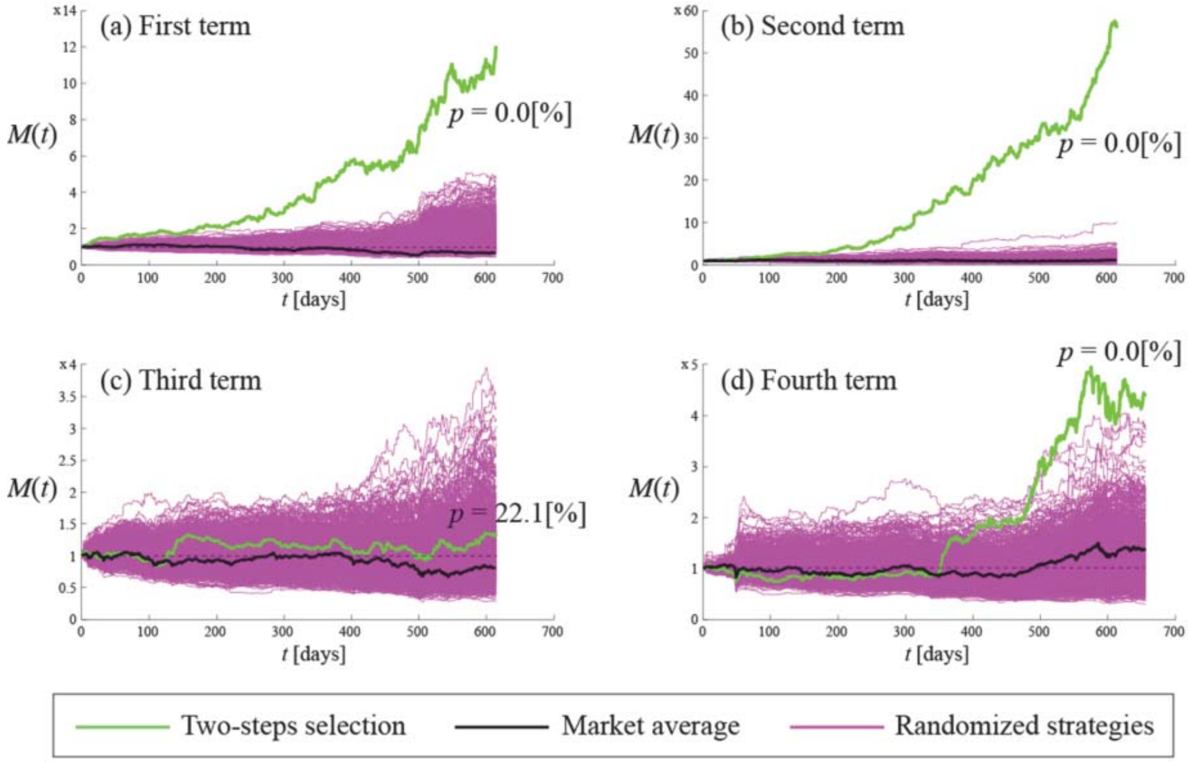
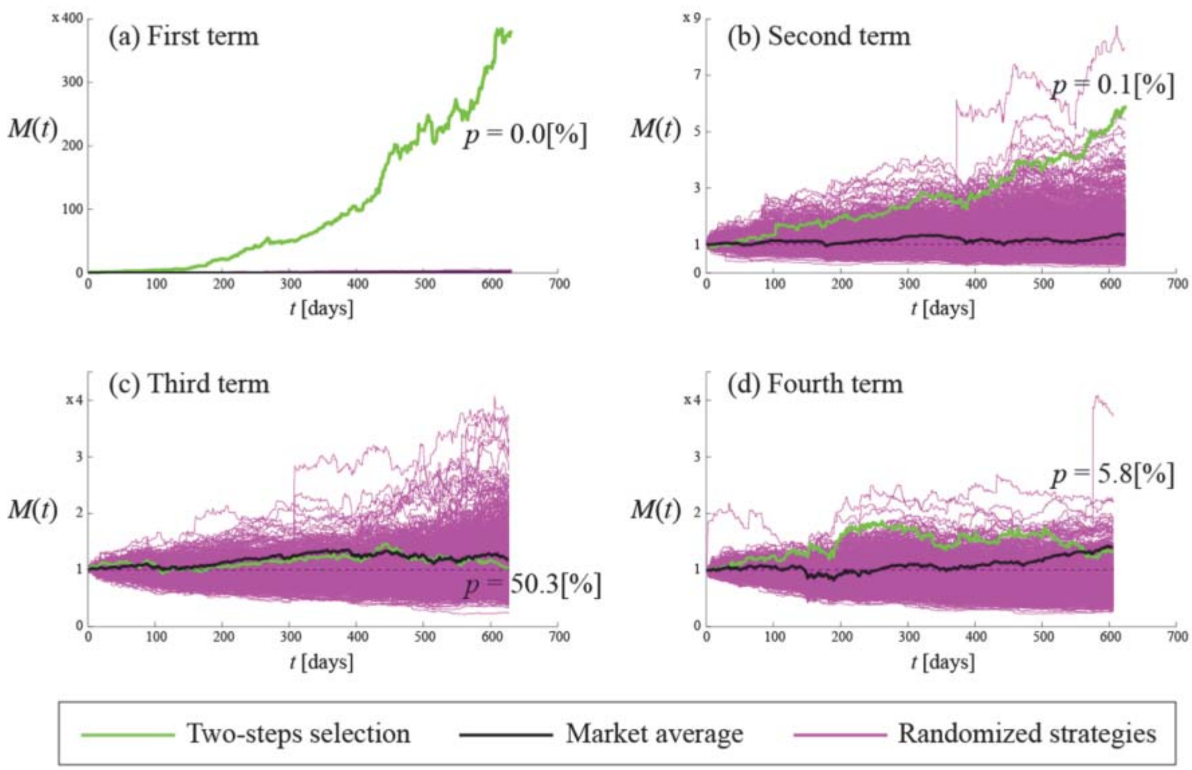


Figure 15. The same as Figure 12, but in the American market (c=0.1[%])



Validity of My Proposed Method

Finally, from the viewpoint of evidence-based technical analysis[7], the statistical significance test is required to show the evidence that the profitable performances shown in Figures 8–15 were not just lucky. For this reason, I compare the original strategy to its randomized strategies.

If my proposed method is truly profitable, it means that the selected stock for each investment was suitable. On the other hand, if the given profitable performances were just lucky, its alternative method that randomly selects a stock for each investment could also sometimes show the same profitable performance. Therefore, I executed this alternative method based on the random stock selection 1,000 times to compare with my proposed method. The results are shown in Figures 8–15, where "Randomized strategies" are the asset growth rates given by the alternative method. Similarly, Figures 8–11 show the results of the additive asset growth rate $M_1(t)$, and Figures 12–15 show those of the multiplicative asset growth rate $M_2(t)$.

Next, to evaluate the advantage of my method quantitatively, I calculate the p-value (i.e., the percentage that the original method was defeated by its alternative methods. For this calculation, the final results of each asset growth rate were compared. According to the statistical significance test, if the p-value is less than 5[%], it can conclude that the profitable performance of my method was not lucky from the statistical viewpoint. This p-value is also shown as p [%] in Figures 8–15. As we can see, except in the third term, the p-value is less than 5[%], even if c=0.1[%], which guarantees the validity of my proposed two-step selection because its profitable performance was better than lucky. However, the third term in both markets seems to be difficult to predict by machine learning approach.

Conclusion

In this thesis, I mixed three techniques to improve trading performance in real stock markets. The first technique is the neural network, which was used to identify complex nonlinear patterns hidden in historical price data. The second one is ensemble learning, which can enhance the predictive power of neural networks. The third one is the two-step stock selection based on my consensus ratio. In particular, the first selection was used as a filter to remove unpredictable stocks in the back test. Then, the second selection adaptively detected more reliable stocks in the forward test because my consensus ratio can indicate the risk of the ensemble learning and can detect more reliable stocks before taking a new position.

To confirm the predictive power and profitability of my framework, I performed some simulations using the real data of 590 stocks listed in the Tokyo Stock Exchange and 500 stocks listed in the New York Stock Exchange. As the result, I could confirm the predictability and profitability in real stock markets if the commission rate is not too large compared to ordinary online brokers, which could be counterevidence to the efficient market hypothesis. Moreover, the common result was confirmed during many terms in two major markets, and therefore it would be general in stock markets.

Notes

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K-Divergence

A Non-Conventional Theory on Gaps—When Are They Significant and How to Trade Them Profitably

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Abstract

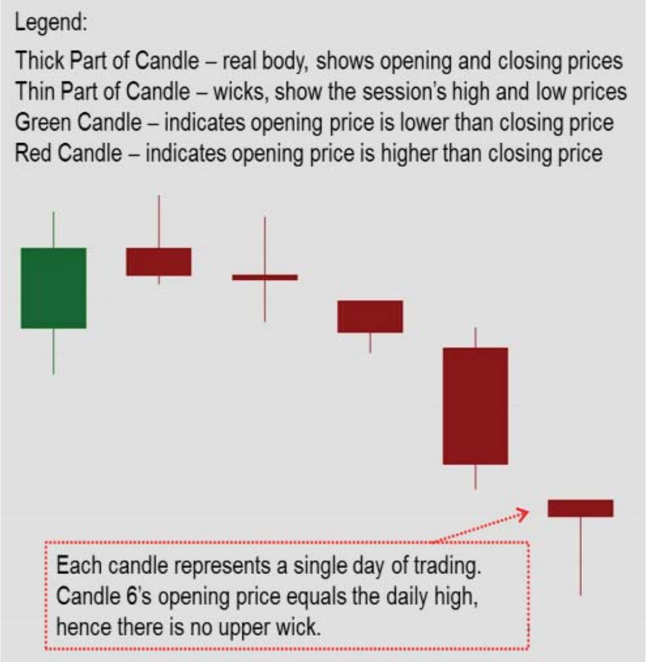
Gaps and windows (or simply "voids"), as they are known by Western technicians and their Japanese counterparts, respectively, represent holes on a price chart, where a trading session's price range lies completely outside the previous session's range. They are truly some of the most conspicuous price phenomena and, as such, they have garnered much attention from the technical analysis community. Not surprisingly, most of the existing literature on voids revolves around trading them as they occur on void day (V-day) and suggests some form of a continuation or a reversal strategy. Traditional and widely accepted classification of the phenomenon (e.g., as "runaway" or "exhaustion") is done based on subsequent price action—meaning it cannot be performed on the day the void occurs, but rather, only in hindsight. Naturally, due to the void's evident mark on a chart, emphasis has been invariably placed on the void itself (i.e., the range of prices it spans over). In this paper, I present an entirely different approach to viewing voids—the K-divergence (K-div) theory, in which the focus of analysis is shifted from the void's price range to the range of prices preceding the void's occurrence. I show quantitatively that systematic strategies based on the K-div theory are profitable and outperform traditional void strategies. Furthermore, I propose an alternative classification system that is based entirely on preceding price action, so that it can be utilized as soon as a void occurs. I conclude by presenting a concrete framework about how technicians should apply the K-divergence theory when analyzing securities on an individual basis. Overall, this research serves as a reference for anyone who intends to employ voids as a part of their trading arsenal.

Introduction

In this research, I have used candlestick charts, as they are extremely useful for conducting void analysis. Refer to Figure 1 below if not fully familiar with this type of chart. All charts were created with the TC2000 software.

Before delving into the subject, I cover the terminology used in this work, as many of the terms may appear to be synonymous; however, for the purpose of this paper, they each have a specific meaning and function.

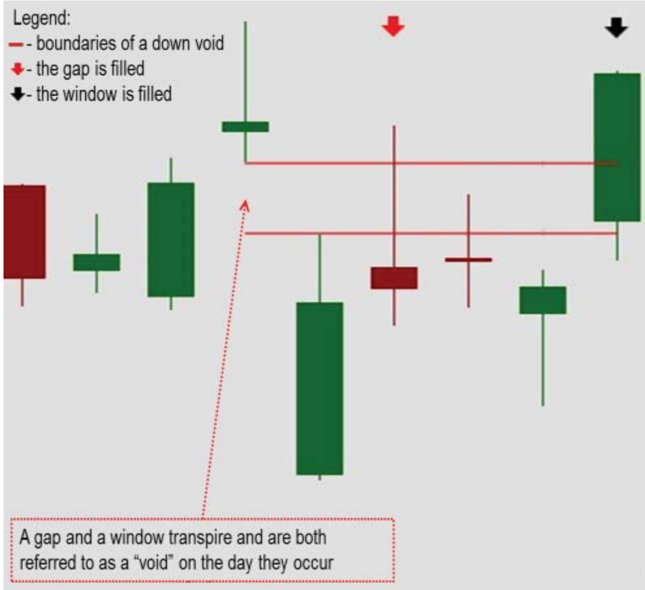
Figure 1. Candlestick chart



Terminology

Upon their occurrence, gaps and windows represent an identical price event—one session's range lying completely outside the previous session's range. They differ, however, in what it takes for them to be considered "filled". A gap is filled when subsequent **intraday** price action retraces the entire range that the gap spans over, while a window is considered filled only if prices **close** beyond the beginning of the window.1 This difference is of significance to many of the tests and strategies in this research. This is why, in order to avoid confusion, I use the term "void" to denote the general idea of prices leaving a hole on a chart (i.e., gaps and windows are referred to as "voids" on the day they occur, up until the moment they get filled). On the other hand, the terms "gap" and "window" are used only when the analysis is concerned with the aforementioned specific difference in their definitions (see Figure 2). In certain situations, I use the term "void filling", which simply indicates prices overlapping the entire length of a void during a trading session (i.e., the session's closing price is irrelevant to the analysis and thus, there is no need to specify if the window was filled along with the gap).

Figure 2. Void terminology



Prelude and Review of Existing Literature

Voids are one of the most easily recognizable price phenomena and as such, they are found in a myriad of technical analysis texts. Many of these texts present a theory about why voids occur and suggest a trading strategy that would be profitable if the theory was indeed true. The propositions are often coupled with a few charts that visually support the suggested theory as if the void is such a rare price pattern that a few examples can be representative of the entire population. In fact, voids appear quite frequently. I examined a list of 448 constituents of the S&P 500 index and found a total of 14,219 voids over a period of 476 trading days (see Materials and Methods section for testing methodology). This means that, on average, there were slightly less than 30 voids a day, which translates to roughly 6.7% of the 448 constituents forming a void on a daily basis. With so many voids transpiring daily, there is certainly no lack of theories trying to explain their emergence.

One of these theories is that voids are continuation patterns and that they should act as support or resistance if prices pull back within their range. Contrary to this supposition is the popular adage that states "all gaps get filled", meaning that upon an occurrence of a void, one should trade against it. Julie Dahlquist and Richard Bauer Jr. (2012), in their *Technical Analysis of Gaps*, have done extensive testing in their attempt to empirically answer the question of whether one should trade in the direction of the void or against it. In their book, they have used the gap definition of a void, thus, I use the term "gap" when discussing their findings. They analyzed a total of 213,932 gaps over a 17-year period (1995–2011) and tested various holding-period returns for implementing a long strategy on the day a gap occurred. They found that, going long, after both up and down gaps, is unprofitable after one day but profitable at the 30-day mark (i.e., upward gaps experience immediate reversal and longer-term continuation implications, whereas downward gaps show immediate continuation and longer-term reversal implications [p. 85]). The results do not seem consistent enough for a strategy to be formulated. Traditional theory does not differentiate between up and down gaps, so unless one expects them to be inherently different, returns should exhibit similar patterns (if not similar returns).

Yet, despite the conflicting theories, there appears to be a consensus among authors and traders about a widely accepted classification system for voids, and an agreement that proper type identification is the key to trading them successfully.[2] Dahlquist and Bauer, along with Robert Edwards, John Magee, John Murphy, Martin Pring and Steve Nison, among many others, have all discussed the same classification system in their texts. It focuses on the void's range of prices and is based on two criteria. Firstly, it depends on the position of the void relative to preceding price action, where the void could be in the same or in the opposite direction of the prevailing trend, or simply be within a trading range. The second criterion is whether the void remains open or it gets filled. Unfortunately, whether a void is filled can only be determined after observing prices subsequent to the void, which means that, ultimately, classification can only be performed in hindsight. Based on the two aforementioned criteria, as per traditional theory, voids can be four types and are deemed as either significant—the "breakaway", "runaway" and "exhaustion" types, or insignificant—the "common" type.

The breakaway type is said to start a new trend, meaning that it appears in the opposite direction of the main trend or upon a breakout from a consolidation area. A mandatory condition is that voids of this variation do not get filled in the short term. They carry continuation trading implications, and the void itself is expected to serve as support/resistance for any pullbacks.

Voids of the runaway (also known as "measuring") type are also not filled in the short term and, just like the breakaway variant, carry continuation trading applications. The difference is that they appear in the direction of the prevailing trend.

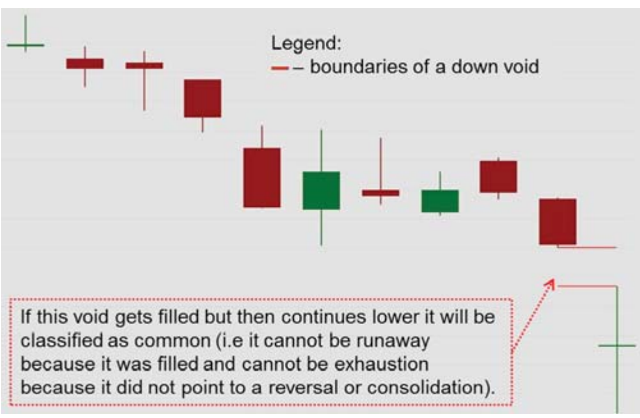
Similar to the runaway, the exhaustion variant appears in the direction of the prevailing trend; however, voids of this type are quickly filled and point to either a reversal or price consolidation.

The common type (also known as "area" or "pattern") is deemed insignificant, as this kind of void is filled quickly and is not expected to produce a trading opportunity. If one examines closely the definitions of the three significant types of voids, they can see that the common type was created as a category for all the leftover voids. Essentially, they are all the voids that do not fit any of the three previously discussed definitions. For example, common voids are the ones that occur in the opposite direction of the main trend, or as a part of a trading range, but are filled quickly thereafter (unlike the breakaway type that remains open). They are also the ones that appear in the direction of the main trend, where they get filled (unlike the runaway type that remains open), but after getting filled, prices continue in the direction of the void (unlike the exhaustion type that points to reversal or consolidation).

There have been numerous suggestions about potential clues, such as volume and the size of the void, for determining the void's type on the day it occurs. However, there is no strictly defined way to differentiate between the aforementioned four types on the day they appear. After all, it is only subsequent price action that can determine the type. The two charts below showcase that the voids in question can be classified only in hindsight, rendering the traditional classification system futile. For a void classification system to be truly useful, it needs to be constructed in such a manner that it can be utilized on the same day that the void occurs.

Figure 3. Breakaway vs. Common void

Figure 4. Runaway vs. Exhaustion vs. Common void



The theory on voids that I am about to present *diverges* significantly from other void theories in the technical analysis literature—hence its name: "K-divergence".

K-Divergence

I theorize that most voids do not occur at significant price levels.[3] Instead, up voids transpire after prices have already moved away from oversold levels and down voids occur after prices have already moved away from overbought levels. As a result, the focus of analysis is shifted from the void itself to the range of prices preceding the void. Two major implications arise. First, support and resistance levels are not expected to be found within the void's range, but rather within the range of prices preceding the void. Second, classification of voids is no longer based on whether they remain open or get filled. Below, I explore how K-divergence (or K-div for brevity) compares to traditional void theory and what its trading implications are.

As discussed earlier, traditional theory places emphasis on the void's range—it classifies voids based on whether they remain open. As per the classification rules, a condition for a void to have continuation implications (i.e., to be labeled as either the breakaway or the runaway type) is that it does not get filled in the short term. This strict requirement seems to imply that these two types of voids result from an unanticipated event, and that the void represents a price adjustment to this event. If the event is of true significance, then the void should remain open. However, if prices were to trade at pre-void levels, then the void, depending on its location, would be classified as either the common or the exhaustion type—neither of which carries continuation implications (see Figure 5).

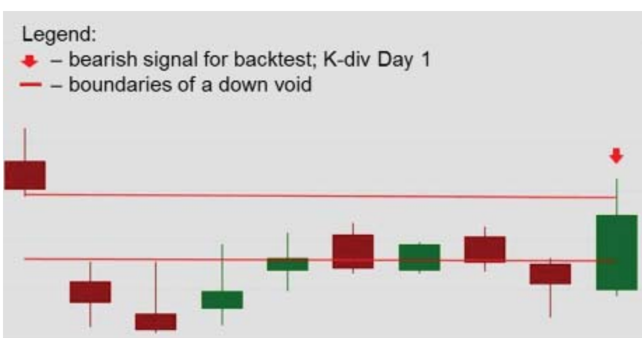
Figure 5. Lam Research Corp (LRCX) daily chart

Contrary to the above supposition, I theorize that in the majority of cases, a void does not span over significant levels, meaning that prices should not find support/resistance within its range. The K-divergence theory is premised on the idea that some market participants act prior to the beginning of notable moves.[4] Thus, when a void transpires due to company-specific news or marketwide events (just to name a couple of plausible reasons for the occurrence of a void), according to K-div, some market players have already acted in the direction of the void. This implies that the truly significant price level lies in a range of prices preceding the void. From here on, in the context of the K-div theory, I refer to the significant level that lies prior to the void's appearance, and is expected to serve as support or resistance, as "K-div support" or "K-div resistance", respectively. The exact location of this theoretical level is unknown. However, it lies within a range of prices that can be objectively determined—referred to as "K-div support/resistance range" (see Figure 6 for an example of a K-div resistance range).

Figure 6. Lam Research Corp (LRCX) daily chart
(Same as Figure 5, plus 13 sessions)

The trading implications of K-divergence are as follows. Once a down void transpires, one would get a bearish K-div signal if prices pull back, fill the void, and reach the K-div resistance. Similarly, once an up void appears, one would get a bullish K-div signal if prices pull back, fill the void and reach the K-div support. As mentioned, the precise level where the K-div support/resistance lies, and from which prices are expected to stall and reverse, is impossible to pinpoint. To backtest a systematic strategy based on K-div, an assumption needs to be made about the exact moment when prices reach the K-div support/resistance. To avoid data mining, I chose to initiate a position during the first session in which prices begin trading within the K-div support/resistance range. I refer to this session as "K-div Day 1" (see Figure 7 for an example of a bearish signal that occurs on K-div Day 1).

Figure 7. Bearish signal on K-div Day 1



This entry implies that the K-div support/resistance level is reached on the same day that the void gets filled. This is assumption certainly does not apply to all cases; however, it provides the least ambiguous entry for the backtest. In the Discussion section, I relax the assumption that all signals should be taken on K-div Day 1 and propose an alternative entry that, depending on the technical picture of the security in question, should be chosen over the one used in the backtest.

So far, it was established that for the purposes of the backtest, a position will be initiated on K-div Day 1. This leaves two options for entry. A position can be initiated either on an intraday basis as soon as the void's range is overlapped (i.e., the gap is filled) or at the close of the session. Based on the two possible entries, I refer to the two strategies as K-div-I (I for "Intraday entry") and K-div-C (C for "entry at the Close"), respectively.[5]

Materials and Methods

Proposed Tests

The quantitative portion of this paper is split into two parts. First, I run tests that aim to provide necessary background on the K-divergence theory and voids in general. Then, I backtest five systematic strategies based on traditional void theories, along with the two aforementioned K-div strategies (K-div-I and K-div-C). All testing was done using Python 3.

Void Statistics Tests

1. Find the average size (in % terms) of all up and down daily moves during the tested period.[6]
2. Find the average size (in % terms) of all up and down voids (the void itself) and the average size of all daily moves with either an up or a down void.
3. Find what percentage of gaps gets filled after they occur. I use the gap requirement for filling since that is a sufficient enough condition to get a K-div signal. I gave each gap 44 trading days (approximately two months) to get filled so that the results have trading applicability.[7]

Void Trading Strategies Backtest

I test the 1-, 2-, 5-, 10-, 20-, 30- and 44-day period returns for the following strategies.

1. Continuation strategy on V-day. Go long at the close of an up void and short at the close of a down void.
2. Continuation strategy on V-day with a stop-loss. Same as Strategy 1; however, exit the trade as soon as the gap is filled during a trading session.
3. Continuation strategy on V-day with a stop-loss. Same as Strategy 1; however, if the window gets filled, exit the trade at the close of the trading session.
4. Reversal strategy on V-day. Go short at the close of a down void and long at the close of an up void.
5. "Fading the Gap" strategy. Same as Strategy 4; however, exit the trade as soon as the gap is filled during a trading session.
6. K-div-I strategy. Go long after a bullish K-div and short after a bearish K-div signal on an intraday basis on K-div Day 1.
7. K-div-C strategy. Go long after a bullish K-div and short after a bearish K-div signal at the close on K-div Day 1.

Backtesting Methodology

To avoid using ambiguous restrictions for volume, liquidity or void size, I chose the S&P 500 index as my testing universe.[8] An imperative adjustment, however, was to exclude any constituent that had undergone a split or a reverse split during the tested period. Using split-adjusted prices was not an option, as such data is also adjusted for dividends and would have resulted in most signals in dividend-paying stocks occurring at different prices than if they were to be executed in real-time. Using stocksplithistory.com, I determined that 448 of the index's constituents had not gone through any splits during the tested period.[9] This meant that roughly 90% of the index's constituents would be included in the test.[10] Using unadjusted data also meant that all ex-dividend voids will be included in the test. Not all dividends result in ex-dividend voids on the daily chart because in many cases, the opening void gets filled during the day. I decided that if an ex-dividend opening void remains open throughout the day (i.e., it becomes a void on the daily chart), it should still be included in the backtest. Excluding ex-dividend voids would have implied certainty that they had remained open throughout the entire trading session solely due to the distribution of the dividend (and not partly due to other factors such as market participants' actions during the session). I decided against making such an unverifiable supposition.

It is important that the proposed strategies are backtested during all market environments (uptrend, downtrend and consolidation). Keeping this in mind, I chose to investigate the period from March 3, 2014, to January 20, 2016. During this period, the S&P 500 had gone through several phases in which it moved uninterruptedly either up or down, or trended within a tight range. Given that some of those phases spanned more than two months, and that the longest holding period in the backtest was 44 days, the entire period under investigation was truly inclusive of all market environments (i.e., the uptrends, downtrends and consolidations were lengthy enough for returns to capture the strategies' performance during such market environments despite the market being essentially flat during the tested period).

When calculating the returns of the seven strategies, the following assumptions were made. First, the strategies that had either a stop-loss (Strategies 2 and 3) or a target (Strategy 5) were annualized as if all trades were held for the entirety of the particular holding period.[11] Second, when testing the two strategies based on the K-div theory (Strategies 6 and 7), prices would sometimes close at a price that appears to be beyond the most obvious K-div support/resistance range. To avoid adding constraints about what qualifies as K-div support/resistance range, I chose not to exclude any signals and thus every filled void resulted in a K-div signal.[12] Lastly, in some cases where price action filled more than one void within the same session, all signals were included in the backtest so that it is truly representative of all voids.

Results

Void Statistics

Tables 1 and 2 summarize the statistics obtained from the tests.

Table 1. Average size of daily moves, voids, and daily moves on days with voids

Size statistics (03/03/2014 - 01/20/2016)						
Direction of move or void	Up void	Move on up void day	Up move	Down void	Move on down void day	Down move
Number of observations	7,200		106,333	7,019		102,414
Average size	0.59%	2.44%	1.09%	-0.71%	-2.76%	-1.14%

Table 2. Number and percentage of gaps filled within 44 days after their occurrence

Void statistics (03/03/2014 - 01/20/2016)			
Type of void	Up	Down	Up + Down
Number of voids	7,200	7,019	14,219
Number of gaps filled within 44 days	5,992	5,908	11,900
Percentage of gaps filled within 44 days	83.2%	84.2%	83.7%
Number of gaps open after 44 days	1,208	1,111	2,319
Percentage of gaps open after 44 days	16.8%	15.8%	16.3%

Void Trading Strategies

Tables 3 and 4 show the results of the seven strategies over the various holding periods.

Table 3. 1-, 2-, 5-, 10-, 20-, 30- and 44-day period returns

#	Strategy type	Number of signals	Average return						
			1-day	2-day	5-day	10-day	20-day	30-day	44-day
1	Continuation strategy	14,219	-0.02%	0.02%	-0.05%	-0.22%	0.00%	-0.31%	-0.46%
2	Cont. w/ gap negation	14,219	-0.04%	-0.04%	-0.08%	-0.14%	-0.21%	-0.23%	-0.39%
3	Cont. w/ window negation	14,219	-0.02%	-0.01%	-0.05%	-0.14%	-0.18%	-0.24%	-0.44%
4	Reversal Strategy	14,219	0.02%	-0.02%	0.05%	0.22%	0.00%	0.31%	0.46%
5	Fading of the Gap	14,219	0.04%	0.04%	0.08%	0.14%	0.21%	0.23%	0.39%
6	K-div-I	12,749	0.11%	0.13%	0.21%	0.24%	0.29%	0.30%	0.48%
7	K-div-C	12,749	0.00%	0.02%	0.10%	0.13%	0.18%	0.19%	0.36%

Table 4. Annualized 1-, 2-, 5-, 10-, 20-, 30- and 44-day period returns

#	Strategy type	Number of signals	Annual return						
			1-day	2-day	5-day	10-day	20-day	30-day	44-day
1	Continuation strategy	14,219	-4.69%	2.69%	-2.46%	-6.28%	0.03%	-2.67%	-2.61%
2	Cont. w/ gap negation	14,219	-8.93%	-4.52%	-4.02%	-3.33%	-2.59%	-1.91%	-2.23%
3	Cont. w/ window negation	14,219	-4.59%	-0.73%	-2.52%	-3.54%	-2.30%	-2.03%	-2.49%
4	Reversal Strategy	14,219	4.81%	-2.62%	2.52%	5.56%	-0.03%	2.63%	2.67%
5	Fading of the Gap	14,219	9.63%	4.92%	4.27%	3.46%	2.67%	1.96%	2.25%
6	K-div-I	12,749	30.97%	18.17%	11.02%	6.33%	3.67%	2.58%	2.77%
7	K-div-C	12,749	0.09%	2.55%	5.17%	3.33%	2.29%	1.61%	2.08%

Discussion

This section is divided into five subsections: Analysis of Results, New Classification System, Alternative Entries, Trading Applications, and Final Tests.

Analysis of Results

Table 1 reveals that moves (in %) on days with voids are much larger than those on days without voids.[13] These results confirm that, on days when voids occur, prices move significantly more than average (i.e., voids are a manifestation of notable moves), and that voids themselves contribute to that increase in size. Table 2 shows that there is a tendency for gaps to get filled (recall that we do not need to close beyond the gap for it to be considered filled). Looking at only the subsequent two months after gaps occurred, the majority were filled (84%).[14] This is in line with the first implication of the K-divergence theory which suggests that the range of prices that voids span over should not act as support/resistance.

Strategy 1 is based on the idea that voids represent continuation patterns. Most of the period returns are negative, with only the two-day return being positive and the 20-day just above breakeven. Strategies 2 and 3 are continuation strategies that assume the void itself serves as a support/resistance. Once the void is filled, the support/resistance is broken and one needs to exit. Strategy 2 uses the gap and Strategy 3 uses the window requirement for filling. Due to its less stringent negation rule, Strategy 3 fares better than Strategy 2 after one, two and five days; however, from day 10 and beyond, it exhibits similar results to those where the gap definition was used. Overall, it is evident that in the very short term (1-, 2-, 5-, and 10-day periods) adding a stop-loss is detrimental to the simple continuation strategy's returns. This can be explained by the large percentage of voids getting filled in the immediate days after their occurrence, resulting in multiple stopped-out trades for Strategies 2 and 3. Looking at the results, it does not become obvious that filling of the void implies that any significant support/resistance level has been broken.

The simple reversal strategy (Strategy 4) is the opposite of Strategy 1. It is evident that during the tested period, the reversal strategy outperformed its continuation counterpart, even though the returns are not consistent enough for a systematic strategy to be implemented. Another popular reversal strategy, "Fading of the Gap" (Strategy 5), aims to profit from the tendency of gaps to get filled. Such a strategy entails entering in the opposite direction of the void at close on V-day, and as soon as the gap is filled, the position is closed out. All period-returns are positive, with the short-term returns being the highest due to the fact that a lot of gaps get filled very soon after they appear.[15]

The data obtained from testing the above five strategies points to a refutation of the supposition that voids carry continuation implications on the day they occur. There were a total of 1,470 voids that remained open throughout the period. However, even they could not boost the continuation strategy enough for it to experience consistent positive returns. Furthermore, the notion that the void's entire range should serve as a support/resistance is not backed up by the results. However, as most gaps get filled shortly after they occur, it was observed that a strategy aiming to fade the gap outperforms the remaining traditional strategies.

The returns of the two K-div strategies (K-div-I and K-div-C) were obtained from a total of 12,749 signals, meaning that almost 90% of all voids during the period ended up giving a K-div signal. Both strategies experienced positive returns throughout all holding-periods. Strategy 6 (K-div-I) outperformed Strategy 7 (K-div-C) meaning that, on average, it was more profitable to initiate a position on an intraday basis as soon as the gap is filled instead of entering at the close of K-div Day 1.[16] See Appendix 1 for a breakdown of the K-div-C strategy based on whether the window remained open or it was filled along with the gap on K-div Day 1.

A question arises regarding whether the returns obtained from the K-div strategies are statistically significant (i.e., are they due to luck or to the strategies' predictive power?). To answer this question, a hypothesis test is conducted where the null hypothesis is that the strategy has no predictive power (i.e., it has an expected return of 0%). Given the sample size and variation of returns, it can be determined whether the returns are high enough to reject the null hypothesis and accept the alternative hypothesis that the strategy has predictive power (Aronson, 2007). I conduct a bootstrapping test on the K-div-C strategy. See Appendix 2 for a description of all assumptions and steps in the bootstrapping test. The results of the procedure show that the K-div-C returns are statistically significant when we look at the 5-, 10- , 20-, 30-, and 44-day returns (with a 5% significance level), meaning that there was less than 5% chance that the returns for these holding periods were due to luck and not the strategy's predictive power.

Table 5. Bootstrap test results

10,000 resampled means	Period						
	1-day	2-day	5-day	10-day	20-day	30-day	44-day
Number of resampled means greater than Strategy 7s mean (average) return	5,281	1,910	44	83	173	430	11
P-value	52.8%	19.1%	0.4%	0.8%	1.7%	4.3%	0.1%

New Classification System

Despite the consistently positive returns obtained from the systematic K-div strategies, I was convinced that the backtest included many signals that should not be taken on K-div Day 1, and others that should not be taken at all. Recall that the K-div is premised on the idea that there are significant price levels (i.e., the theoretical K-div support/resistance) located prior to the void occurring (see Figure 8).

Figure 8. Rockwell Automation Inc (ROK) daily chart

In this case, one can objectively identify the K-div resistance range, as the void appears shortly after a top has formed. Also, one can determine the exact negation level of the bearish K-div signal (i.e., the upper boundary of the K-div resistance range). Let's look at the same chart, now in the context of a different down void.

Figure 9. Rockwell Automation Inc. (ROK) daily chart

The highlighted void in the above chart occurs after a prolonged move. When prices pull back to give a bearish K-div signal (red arrow), we are nowhere near the high from where the descent began, meaning that the K-div resistance could lie anywhere within the entire move (i.e., the K-div resistance range is broad). Initiating a position on K-div Day-1 implies confidence that there is resistance nearby, something that is not apparent in this case. If prices continue upwards, it is very likely that one will close out the position before prices have reversed to the downside. To filter out such cases systematically, a modification of the previously tested K-div strategies is required. This is when a new classification system for voids can come in handy. A new system that is not based on subsequent price action but, rather, on already available data, thus allowing implementation as soon as a void occurs (i.e., on V-day).

I propose a new classification system where the void is categorised strictly based on its location relative to a price range preceding the void. The creation of such a system is a substantial project in and of itself and is not in the scope of this paper. For the purposes of this work, I present a simplified version of such a system—one that serves two purposes. First, it provides a way to filter out a particular set of K-div signals. Secondly, and more importantly, it aims to demonstrate the trading applicability of a classification system that can be utilized as soon as a void occurs.

The goal of the system is to categorize voids in such a way that only up voids that appear near a recent bottom and down voids that occur near a recent top are used, allowing for a more objective K-div support/resistance range identification. The simplest version of the system is placing all voids into the following four categories: low-up, high-up, low-down, and high-down voids. Classification is based on the closing price of the security on V-day relative to the range of prices preceding the void.

I utilize the proposed classification system as a filter, where I only take the bullish K-div signals given on low-up voids and the bearish K-div signals given on high-down voids. For the following test, I chose a 44-day period to determine the pre-void trading range and a 50% threshold level to determine what bucket each void would go into (see Table 4). For example, if a stock closed at $40 on a day with a down void, and the trading range over the 44 days before the void's occurrence was $30–$43, then the void will be labeled as a high-down void because it closed in the upper half of the preceding trading range (i.e., it closed at roughly the 77th percentile of the preceding range: (40–30) / (43–30) = 76.9%).

Table 6. Proposed classification system for voids (simplified)

Simplified classification system			
Classification	**Direction of void**	**Closing price on V-day falls in...**	**Figure #**
Low-up void	Up	lower half of preceding 44-day price range	Figure 11
High-up void	Up	upper half of preceding 44-day price range	Figure 10
Low-down void	Down	lower half of preceding 44-day price range	Figure 11
High-down void	Down	upper half of preceding 44-day price range	Figure 10

See the figures below for examples of each void.

Figure 10. Examples of high-up and high-down voids

Figure 11. Examples of low-up and low-down voids

To be fair to all proponents of voids being a continuation pattern, besides retesting the K-div-I and K-div-C (Strategies 6 and 7), I also retested the simple void continuation strategy (Strategy 1) with the same filter (i.e., buy only after low-up voids and short only after high-down voids, while ignoring high-up and low-down voids). The rationale is the following: entering in the direction of the void on V-day in the expectation that it will remain open, while at the same time, eliminating any possibility of entering after the exhaustion variant (since exhaustion voids appear in the direction of the prevailing trend and the filter avoids such voids).

Below, I discuss the results of the three strategies, now utilizing the proposed classification system as a filter.

Table 7. 1-, 2-, 5-, 10-, 20-, 30- and 44-day period returns with filter

Strategies with filter									
#	Strategy type	Number of signals	Average return						
			1-day	2-day	5-day	10-day	20-day	30-day	44-day
1	Continuation strategy	3,991	-0.13%	-0.04%	-0.02%	-0.10%	0.11%	0.17%	0.16%
6	K-div-I	3,729	0.07%	0.10%	0.20%	0.34%	0.37%	0.54%	0.83%
7	K-div-C	3,729	0.03%	0.06%	0.17%	0.31%	0.33%	0.50%	0.80%

Table 8. Annualized 1-, 2-, 5-, 10-, 20-, 30- and 44-day period returns with filter

Strategies with filter									
#	Strategy type	Number of signals	Annual return						
			1-day	2-day	5-day	10-day	20-day	30-day	44-day
1	Continuation strategy	3,991	-27.83%	-4.83%	-1.04%	-2.42%	1.44%	1.40%	0.90%
6	K-div-I	3,729	18.51%	12.87%	10.70%	8.99%	4.77%	4.60%	4.87%
7	K-div-C	3,729	9.13%	8.11%	8.73%	7.98%	4.28%	4.26%	4.64%

All three strategies used the same set of voids—a total of 3,992 voids fit the criteria. Out of those, 93.4% (3,729) ended up giving a K-div signal. The returns from the simple continuation strategy are once again mixed, being quite negative at Day 1, and then gradually improving to finally turn slightly positive after the 20-day mark. When compared to the same strategies without a filter, the K-div-C strategy experiences improved returns over all periods, and the K-div-I strategy after the 10-day mark. As hypothesized, using the proposed classification system improved the returns of the K-div strategies.

Having quantitatively proven that strategies based on the K-div are profitable, I now present specific examples that demonstrate how I utilize the theory when examining securities on a case-by-case basis.

Trading Applications

The discussion below is from the perspective of a bullish K-div signal. A bearish K-div mirrors the bullish signal on the short side.

As already pointed out in the New Classification System subsection, the up void should occur in proximity to a recent low. The low may be a major one, or simply the lowest point of a consolidation pattern. The closer the up void to that low, the more objective it is to determine where K-div support may lie. This would also aid in the implementation of an exit strategy if prices move lower (i.e., against the bullish K-div signal). In most cases, this would imply selling as soon as prices close below the preceding low. Looking at the reward side of the equation, bullish K-div signals that point to a reversal of prolonged downtrends or those that indicate a price continuation to new highs should, in general, be preferred over signals that occur just below major overhead resistance. Lastly, it is preferable, yet not required, that a violation of a well-defined downtrend is observed prior to the bullish K-div signal occurrence. This does not necessarily mean that the bullish K-div can only be used as a reversal signal at the end of major downtrends. The violated downtrend could be within a corrective move, and its violation—pointing to a continuation of the main uptrend. The two charts below are good examples of bullish and bearish situations that fit the aforementioned criteria. It is important to note that all K-div signals, which are based on the supposedly insignificant common voids, occurred prior to the appearance of various breakaway and runaway voids.

Figure 12. Prudential Financial Inc. (PRU) daily chart

Figure 13. Hewlett Packard Enterprise Company (HPE) daily chart

Often, I look for K-div signals occurring alongside traditional Western patterns. The benefit of doing so is that, by looking at the boundaries of the pattern, one can objectively determine a recent top/bottom that is then used as a negation level for closing out the K-div position. This use of K-divergence is also where the theory diverges most significantly from traditional void theory. While, as per widely accepted classification rules, voids would be dismissed as insignificant (i.e., will be categorized as "common"), K-div produces signals with very favourable risk-reward profiles. Below, I discuss two scenarios in which a K-div signal appears alongside first, a Head and Shoulders (H&S) pattern, and then, a rectangular range.

The H&S pattern is one of the most widely recognized and most disputed patterns in technical analysis. One of its most significant drawbacks is its stringent, yet ambiguously determined, rule for entry upon breaking of the neckline on a closing basis. It is often the case that, by the time prices close beyond the neckline, the move has already been underway for a long enough period to lead to an unfavourable risk-reward ratio of the trade. One way to tackle this is to wait for a pullback after the breakout, since common wisdom suggests that price may retrace to the neckline before reversing in the direction of the H&S signal. Unsurprisingly, it is not always the case that price pulls back to the neckline since it sometimes goes beyond the neckline, and at other times falls short of it. *Here, I propose that if a void transpires during the formation of the head or the right shoulder, or upon breaking out of the pattern, a probable scenario is that price will pull back to pre-void levels, giving a K-div signal (instead of retracing to the neckline).* The chart below depicts two H&S and two inverse H&S patterns, in which not a single time do prices retrace exactly to the neckline after breaking through it.

Figure 14. Fifth Third Bancorp (FITB) daily chart

Furthermore, in all cases, entries upon K-div signals were more favorable from a risk-reward standpoint than those given by the traditional H&S signal (i.e., breaking of the neckline).

Some of the most effective K-div signals are given within a trading range. Figure 15 depicts one such setup, where prices trade within a horizontal range after violating a trendline. This is when I start looking for K-div signals in the opposite direction of the broken trendline. Given the negation level, there is a significantly improved risk/reward profile of the K-div trades when compared to entering upon a breakout of the pattern. Also, a recurring theme is observed—K-div signals preceding the occurrence of breakaway and runaway voids.

Figure 15. Boeing Co. (BA) daily chart

Alternative Entries

In the previous subsection, I discussed some of the conditions under which the K-divergence theory is most applicable. Assuming one has observed such a setup, the question becomes when to initiate a position.

To keep the trade entry objective during the backtests, the only entries discussed up until this point are those of the K-div-I and K-div-C strategies (i.e., as soon as the gap is filled or at the close on K-div Day 1). In reality, I use various intraday strategies when executing on K-div Day 1. Most commonly, once the gap is filled on an intraday basis, I wait for further confirmation that prices are about to reverse in the direction of the K-div signal. So as not to significantly deviate from the topic of voids, these strategies will not be discussed in this paper. However, the goal is clear: initiating a position at a more favourable price than the one obtained by the original intraday entry.

An alternative entry, when analyzing securities on an individual basis, is to initiate a trade after K-div Day 1. This is advisable if a technician is not convinced that prices will reverse immediately after the K-div signal and is looking for further technical confirmation before taking the trade. As previously mentioned, a situation where I usually do not execute on K-div Day 1 is when the K-div support/resistance range is very broad (i.e., the risk on the trade is high). In such cases, if prices continue to push further into the K-div support/resistance range, the risk diminishes, as prices are now closer to the trade's negation level. Figure 16 depicts such a situation where it is prudent to wait for prices to push further into the K-div resistance range so that the potential loss on the trade is reduced.

Figure 16. General Dynamics Corp (GD) daily chart

The charts that were presented in the last two subsections showcase a key point about K-div. Utilizing the theory does not mean simply waiting for any void to be filled. Instead, it requires a thorough K-div support/resistance analysis, which should result in a favourable risk-reward profile of the trade.

Final Tests

The results from the conducted tests demonstrated that, over a relatively long period, a systematic strategy based on K-divergence is consistently profitable and outperforms traditional void strategies. But would the strategy perform as well during much shorter periods in which the broader market moves primarily in one direction? For example, when the market experiences a sharp fall, more down voids remain open (in which case no bearish K-div signal is given) and most up voids will get filled (giving a bullish K-div signals in a falling market). I tested to see how the K-div-I and K-div-C strategies perform over such periods during which the S&P 500 experiences a significant move (either up or down). I studied two 100-day periods during which the index either moved down (05/12/2011–10/03/2011, referred to as the "Downtrend period") or up (11/15/2012–04/11/2013, referred to as the "Uptrend period") by roughly 20%. Without overcrowding this paper with any additional tables, I highlight some key observations from this test below (for more information on this test or any other part of this work, you can contact me at k.divergence@gmail.com).

- The K-div-C strategy is consistently profitable during both periods (ranging from 1.6% to 41.2% annualized), with only the 44-day return during the Downtrend period being negative (-3.6% annualized).
- The K-div-I strategy underperforms the K-div-C strategy during the Downtrend period but outperforms it during the Uptrend period. This supports the recommendation given in the Alternative Entries section that one should not always enter on an intraday basis as soon as the gap is filled.
- Lastly, I tested the simple continuation strategy (Strategy 1). Its returns are positive during the Uptrend period (excluding the 1-day return) but negative throughout the Downtrend period.

Conclusion

After examining the results from the tests within this work, it did not become clear to the author whether on V-day one should trade in the direction of the void or against it. However, strategies based on K-divergence experienced consistently positive returns during all tested periods.

The editorial note for the ninth edition of Edwards and Magee's (2007, p. 230) *Technical Analysis of Stock Trends* states the following: "The truth is there is nothing more that need be said about gaps, and the truth also is that no modern examples need be added". The goal of this paper was to show that there is more to the void phenomenon than what is currently available in the technical analysis literature.

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Notes

[1] Windows are usually referred to as "closed" and not "filled", but I use the term "filled" to avoid confusion when discussing closing prices.

[2] In most books, the classification system is not concerned with the closing prices on the day the void's range is filled, thus I use the term "void" when referring to the classification system.

[3] I refer to price levels that are expected to serve as support or resistance as "significant".

[4] It is not important to specify (or speculate about) who the market participants are that act prior to the beginning of notable moves. It could be insiders, exceptional fundamental or technical analysts. What is important, however, is the assumption that events, which cause voids to occur, are anticipated by a certain portion of market players (and that they have already traded in the direction of the void before it has occurred).

[5] Note that the entry price for each strategy can be objectively determined and backtested. For example, the K-div-I strategy initiates a trade as soon as a gap is filled. There are two ways for a gap to get filled on K-div Day 1. Firstly, it can get filled as prices move through the gap's range and reach its beginning. In this case, the entry price is the beginning of the void, which price is known in advance of K-div Day 1(i.e., it is known on Void Day). The second way for the gap to get filled is if on K-div Day 1 prices open beyond the beginning of a gap, meaning that the gap is filled immediately at the open (i.e., entry is executed at the open). Both of these scenarios can be objectively tested. In the case of the K-div-C strategy, entry takes place at the close on K-div-Day 1.

[6] A daily move represents the % change in price over two trading sessions (using closing prices).

[7] If anyone wanted to "fade the gap", it is unlikely that they would wait six months for the gap to get filled.

[8] All S&P 500 constituents are highly voluminous and liquid. Furthermore, they are not allowed to have very low prices and are required to have a market cap in excess of 4 billion.(http://www.spindices.com/documents/factsheets/fs-sp-500-ltr.pdf)

[9] Some of the constituents in the backtest are no longer part of the index. However, all companies have been part of the index during the tested period.

[10] Since the S&P 500 index includes more than one type of common stock for five companies, only one ticker per company was included.

[11] For example, when calculating the 10-day return for Strategy 5, if a gap was filled after two days, the return was annualized as if the trade was not closed until Day 10. Annualizing the return after two days would have assumed one can replicate the return five more times within the 10-day period. This is not possible, as there is a limited amount of voids and each void is already included in the test.

[12] In the rare cases that prices closed at an all-time high on K-div Day 1, we would still get a bearish K-div signal even though prices have closed above the K-div resistance range.

[13] As can be seen from Table 1, moves on days with down voids (-2.76%) were over 2.4 times greater than the average down move (-1.14%), whereas moves with up voids (2.44%) were over 2.2 times greater than the average up move (1.09%). The up and down voids during the period had an average size of 0.59% and (-0.71%), respectively.

[14] Dahlquist and Bauer (2012) conducted similar research. They found that during the January 1—June 30, 2010, period, out of 10,766 gaps, only 4% of up gaps and 3% of down gaps did not get filled by the end of December 2011. The difference in results is due to the fact that they allowed each gap, depending on when it occurred during the tested period, considerably more time for it to get filled—from a year-and-a-half to two years' time.

[15] "Fading of the Gap" strategy yields opposite returns to those of the continuation strategy with negation as soon as the gap gets filled.

[16] The difference in returns (on nonannualized basis) between the two strategies is equivalent to the same-day return for the following strategy—going long on an intraday basis as soon as an up gap is filled, then exiting at the close of day; and going short on an intraday basis as soon as a down gap is filled, then covering the position at the close. The results point to an average 0.10% same-day return over the tested period, leading to the higher K-div-I returns.

Appendices

Appendix A

Breaking Down the K-div-C Strategy

Strategy 7 (K-div-C) entails opening a position at the close on the day that the void gets filled (i.e., at the close on K-div Day 1). Below, I break down all K-div-C signals based on how the void gets filled. I do this to check if sessions during which prices fill the gap but pull back to leave the window open carry different forecasting implications from those sessions that fill both the gap and the window. In the first case, if the gap is filled but the window remains open, the signal is referred to as K-div-G ("G" stands for gap). See Figures A and B for a bearish and bullish K-div-G signals, respectively.

Figure A. Bearish K-div-G

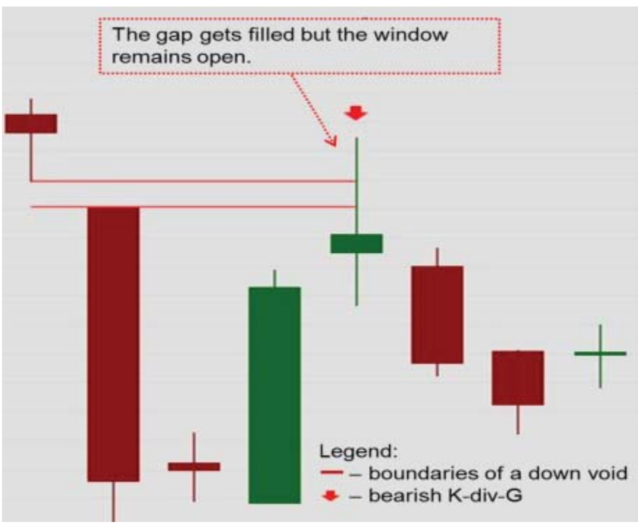
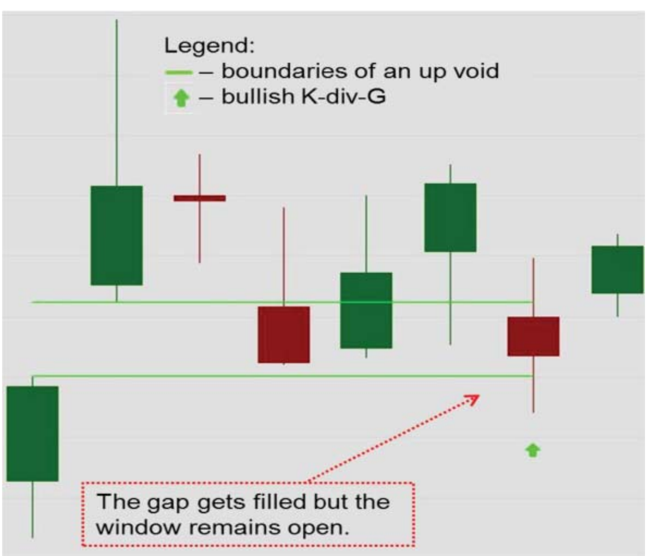


Figure B. Bullish K-div-G



Alternatively, if both the gap and the window are filled during the same trading session, then a K-div-W signal ("W" for window) is observed. See Figures C and D for bearish and bullish K-div-W signals, respectively.

Figure C. Bearish K-div-W

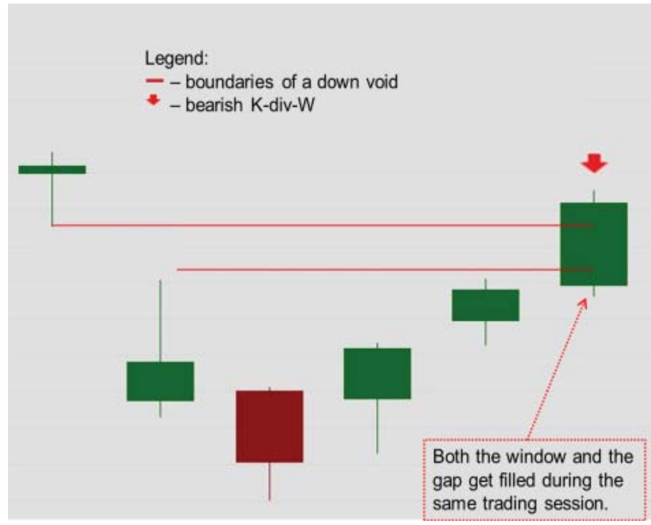
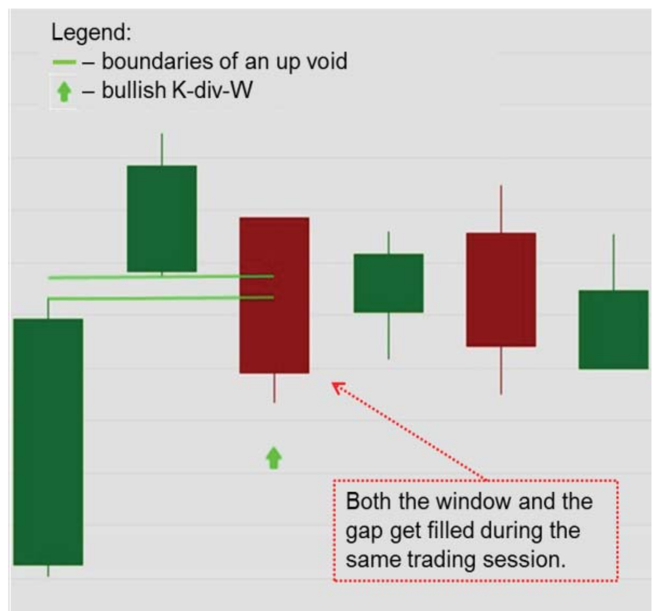


Figure D. Bullish K-div-W



Tables A and B contain the returns from the two strategies.

Table A. K-div-W and K-div-G 1-, 2-, 5-, 10-, 20-, 30- and 44-day returns

Breakdown of K-div-C								
Strategy type	Number of signals	Average return						
		1-day	2-day	5-day	10-day	20-day	30-day	44-day
K-div-W	6,688	-0.009%	0.005%	0.033%	0.168%	0.175%	0.264%	0.535%
K-div-G	6,061	0.011%	0.045%	0.175%	0.096%	0.179%	0.113%	0.177%

Table B. K-div-W and K-div-G annualized 1-, 2-, 5-, 10-, 20-, 30- and 44-day returns

Breakdown of K-div-C								
Strategy type	Number of signals	Annual return						
		1-day	2-day	5-day	10-day	20-day	30-day	44-day
K-div-W	6,688	-2.19%	0.58%	1.65%	4.32%	2.23%	2.24%	3.10%
K-div-G	6,061	2.93%	5.78%	9.21%	2.44%	2.28%	0.95%	1.02%

The 1-, 2-, and 5-day returns of the K-div-G strategy are higher than the K-div-W strategy. Starting from day 10 and onward, higher K-div-W returns are observed (except for the almost equal 20-day return). A probable reason is that for many of the K-div-G signals, prices bounce off K-div support/resistance levels within the same session that the gap is filled and thus reverse immediately, leading to higher shorter term returns.

Appendix B

Bootstrap Test

To determine whether the returns of the K-div-C strategy are due to its predictive power, the Bootstrap Test for evaluating a single rule/strategy was used. David Aronson discusses the procedure in great detail in his *Evidence Based Technical Analysis* (p. 236). In the book, he also presents a framework—a modified White's Reality Check—for testing a strategy's predictive power obtained through data mining (p. 325). Naturally, it is easier for a strategy to "pass" the former test than the latter one. Since I had not originally meant to run a significance test on the K-div strategies, some assumptions were necessary when deciding which of the two tests should be run (i.e., the bootstrap test for a single rule or the modified test for strategies obtained through data mining).

Bootstrap test assumptions

1. A total of seven strategies were backtested. However, the five traditional strategies were only presented for comparative purposes (i.e., I wanted to see how the K-div strategies fare in comparison to traditional strategies). After all, this paper aimed to validate a new theory on voids—K-divergence, and not to engage in data mining so as to find any profitable strategy. Therefore, I decided not take the five traditional strategies into account when conducting the bootstrap test.
2. Due to its intraday entry, the K-div-I strategy has some inherent issues when it comes to running the bootstrap test on it. For example, sometimes a gap is filled right at the open of a trading session, and other times just before the close, resulting in returns that are not truly comparable with one another (i.e., the 1-day return of the former signal is based on almost two days of data, whereas the 1-day return on the latter signal is based on roughly one day of data). Furthermore, the bootstrapping test is usually run on de-trended data, and thus, testing the K-div-I strategy would have required additional assumptions since positions are not initiated at the close of the session. Lastly, given the fact that I wanted to be conservative in my evaluation, I chose to run the bootstrap test only on the K-div-C strategy (i.e., on the strategy with the lower returns).

3. In his book, Aronson evaluates various binary strategies (i.e., one can hold only a long or a short position) on the S&P 500 index. To adjust for any position bias that a strategy may have, each strategy's return is calculated on de-trended S&P 500 data. The K-div-C strategy's returns are not based on the index itself but on 448 of its constituents. Therefore, for the purposes of the bootstrap test, I recalculated the K-div-C returns on de-trended data for each of the constituents (i.e., each constituent's average daily return is 0%). See Table C for the recalculated returns on de-trended data.

Table C. Strategy 7 (K-div-C) returns on de-trended data

Strategy	Number of signals	Average return on de-trended data						
		1-day	2-day	5-day	10-day	20-day	30-day	44-day
K-div-C	12,749	-0.001%	0.020%	0.090%	0.114%	0.138%	0.133%	0.276%

4. Lastly, it is worth noting that the K-div-C is not a binary strategy, as sometimes there are no signals given (neutral position), and other times there are multiple signals given during the same session.

Bootstrap test steps

The steps below are conducted for each holding period.

1. Since the null hypothesis is that the K-div-C strategy has no predictive value, its returns are "zero-centered". This is a simple operation where the mean return of the strategy is subtracted from each observation (i.e., from each individual return) and stored in a list of zero-centered returns with a mean return of 0%.
2. The K-div-C has 12,749 observations. Thus, I sample with replacement 12,749 returns (from the zero-centered list) and obtain a single "resampled" mean return.
3. Step 2 is repeated another 9,999 times and we obtain a total of 10,000 "resampled" means.
4. A sampling distribution is formed of all 10,000 "resampled" means.
5. I test to see how many of the 10,000 "resampled" means are greater than the strategy's mean return. For example, if 4% of the "resampled" means are greater than the strategy's mean return (i.e., the p-value is 4%), then it can be concluded that there is a 4% chance that the strategy's mean return was due to luck. In this case, the null is rejected, and the alternative that the strategy has predictive power is accepted.

M-Oscillator

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Abstract

This paper proposes a new technical analysis tool, the M-Oscillator. This tool can be applied to market indices/securities and can be used for forecasting purposes. The paper also offers a discussion about limitations of the original momentum oscillator and addresses those limitations through this new oscillator.

The M-Oscillator is a bounded oscillator that moves between (-14) and (+14), it gives early buy/sell signals, spots divergences, displays overbought/oversold levels, and provides re-entry points, and it also work as a trend identifier.

Introduction

The Main Concepts of M-Oscillator

Part one presents the concepts of Quantization, Cycle Characteristics and Oscillation. These are the three main concepts of the M-Oscillator.

Quantization

To be able to study the pattern of price movements, we need to analyze two major concepts:

- The magnitude of price movement, which is measured by the change between two consecutive closing prices. This change is called Delta and is signified as Δ. The equation is:
  Δ Closing Price = Closing price (t) – Closing Price (t-1)
- The direction of price movement determines the outcome of the previous equation. A positive value means that the price is increasing relative to the previous day; a negative value will indicate a decreasing price; zero change is the result of flat or no movement in the closing price.
- Quantization is a process of smoothing the magnitude of price movement in a continuous progressive varying series of data. The focus here will be more on the change in the direction rather than the magnitude of the movement. For a set of continuous progressive data, it is important to categorize the contents into three different classes:
- First class is for the positive movements, to which a value of **+1** will be assigned.
- Second class is for the negative movements, to which a value of **-1** will be assigned.
- Third class is for the flat movements, to which a value of **0** will be assigned.

This will allow us to alleviate volatility in the price magnitude. The analysis will be based only on the price direction, regardless of the magnitude of the move.

Cycle Characteristics

There are two repetitions in a price cycle: Troughs and Crest. All trends of the markets are observed as a series of cycles. The variations in cycles occur at the crest and not at the troughs. The cycle crest acts differently depending on the trend; if the trend is up, the cycle crest shifts to the right of the ideal midpoint (right translation), and if the trend is down, the cycle crest shifts to the left of the midpoint (left translation). When we put this into perception, bull trend prices will spend more time going up than down and less time correcting from it; bear trend prices will spend more time going down than up (trend definition).

The main aim of such a method is to display the direction of the price motion over time and isolate or reduce the magnitude of changes of price motion (taking into consideration only the direction of the change in closing prices).

Oscillation

The oscillators in technical analysis are tools that are bound between two extreme values, and they fluctuate above and below a centerline or between the two bands.

The importance of the oscillator:

- Used as a leading indicator to inform us about a possible start or reversal in market direction.
- Describes the strength or the weakness of the trend.
- The best time to use it is during non-trending markets where the prices fluctuate in a trading range.
- The oscillator becomes extremely valuable ally by alerting about the short-term market extremes.
- It can also warn that the trend is losing its acceleration ahead of the price action.
- Indicates any divergence between the oscillator and the price action.
- Crossing the midpoint line gives a signal of the direction of the trend.

Methodology

Introducing the M-Oscillator

This section represents the method used for constructing and implementing the M-Oscillator. Commonly known as momentum oscillator, it is the analysis of the price change rather than the price level; in other words, it is the difference between prices at two time intervals. It is a leading indicator of price direction; it can identify when the current trend is no longer maintaining its same level of strength or is losing momentum. The importance of the momentum is when its value reaches to extreme levels either up or down.

The calculation of momentum is:

Momentum = Ct – C n days ago

Where, Ct is last closing price and Cn is the closing of n days ago

Then positive and negative values are plotted above and below the zero line.

The following is the outcome of revising and analyzing the momentum oscillator:

The advantage

- The momentum line leads the price action (it leads the advance or decline in prices).
- The crossing of the zero line is considered as a trading signal.

The disadvantage

- The need for an upper and lower boundary.
- If recent price gains are the same as older price gains, the momentum line will be flat even though the market is still going up.
- If recent price gains are less than those of before, even if prices are still rising, the rate of change will have slowed further, and the momentum line will actually drop.
- Using price differences in the erratic movements often caused by sharp changes in the value.

The Calculation

This section indicates the possible ways for improving and solving the problems associated with momentum. The direction of the price movements signifies the outcome from the differences between two consecutive days. A positive value means that the price is increasing relative to the previous day; a negative value indicates a decreasing price; zero change is the result of flat or no movement in the closing price. In this study the no movement or flat change in price will be considered as a flat movement.

Steps in calculating the M-Oscillator

1. Compare today's closing price (P_0) with yesterday's closing price (P_{-1}). If $P_0 > P_{-1}$ then a value of 1 is registered; if $P_0 < P_{-1}$ then a value of -1 is registered. 0 is registered if both prices P_0 and P_{-1} are the same. The registered value will be referred to as "t0".
2. Then we compare today's closing price (P_0) with the day before yesterday's closing price (P_{-2}). If $P_0 > P_{-2}$ then a value of 1 is registered; if $P_0 < P_{-2}$ then a value of -1 is registered. 0 is registered if both prices P_0 and P_{-2} are the same. The registered value will be referred to as "t1".
3. Steps 2 are repeated until we reach t13. (If $P_0 > P_{-14}$ then a value of 1 is registered; if $P_0 < P_{-14}$ then a value of -1 is registered. 0 is registered if both prices P_0 and P_{-14} are the same).
4. The sum of ($t_1 + t_2 + t_3 + \ldots + t_{13}$) gives us the value V_0. (Max +14 $\geq V_0 \geq$ min -14).
5. V0 the result of Step 4 will be computed each day going forward to obtain a value (V_n). All these values (V_n) will be connected to form a line.
6. Calculate 5 Exponential Moving Average (EMA) of the line from Step 5.
7. Calculate 3 EMA of the EMA from Step 6 (this will be the main line of M-Oscillator).
8. Calculate 3 EMA of the EMA from Step 7 (this will be the signal line of M-Oscillator).

Mathematical formula

M-Oscillator = 3-day EMA (5-day EMA (V_n))

Signal line = 3-day EMA (M-Oscillator)

Where,

P_0 = Today's closing price

P_{-1} = Previous closing price

$t_0 = P_0 - P_{-1}$

$t_1 = P_0 - P_{-2}$

.

.

$t_{13} = P_0 - P_{-14}$

$V_n = t_n + t_{n+1} + t_{n+2} + t_{n+3} + \ldots + t_{n+13}$

5-day EMA = 5-day Exponential Moving Average of the main line V_n

3-day EMA = 3-day Exponential Moving Average of the 5-day EMA

The following table represents the steps used for the calculation and construction of the oscillator.

- Column 2 represents a 15-day closing value
- Column 3 represents the results (as shown), which are negative, positive or neutral
- Column 4 represents up move (+1), down move (-1), neutral (0)

Table 1. The M-Oscillator Calculation

	Day	Closing price	Δ	Quantization
X15 - X1	X1	13.58	-1.55	-1
X15 - X2	X2	13.28	-1.25	-1
X15 - X3	X3	12.74	-0.71	-1
X15 - X4	X4	12.48	-0.45	-1
X15 - X5	X5	12.81	-0.78	-1
X15 - X6	X6	12.91	-0.88	-1
X15 - X7	X7	12.72	-0.69	-1
X15 - X8	X8	12.59	**-0.56**	**-1**
X15 - X9	X9	12.32	**-0.29**	**-1**
X15 - X10	X10	12.14	**-0.11**	**-1**
X15 - X11	X11	12.03	0	0
X15 - X12	X12	12.02	**0.01**	**1**
X15 - X13	X13	11.97	**0.06**	**1**
X15 - X14	X14	11.82	**0.21**	**1**
	X15	12.03		**-7**

Number of (-) days=10

Number of (+) days=3

Number of (Flat) days=1

So we will allocate the value of **(-7)** to X15.

The M-Oscillator double smoothed those results by n-day EMA “introduced by William Blau, 1995”. Applying the Quantization concept to replace a certain positive value by (+1) and a certain negative value by (-1) and flat movements by zero, gives the M-Oscillator important edges over the momentum oscillator:

- It is a bounded oscillator from (-14) to (+14) because the maximum value to the upside is +14 (when the previous 14 days are positive), and the maximum value to the downside is -14 (if the previous 14 days are negative) while the momentum is unbounded.
- It smooths the price volatility.
- M-Oscillator takes into consideration the intra-period “14 Days”, whereas the momentum ignores it.

The Use of M-Oscillator

Interpretation

- M-Oscillator is plotted along the bottom of the price chart; it fluctuates between positive and negative 14.
- Movement above 10 is considered overbought, and movement below -10 is oversold.
- In sharp moves to the upside, the M-Oscillator fluctuates between 5 and 14, while in down side it fluctuates between -5 and -14.
- In an uptrend, the M-Oscillator fluctuates between zero and 14 and vice versa.

Trading tactics

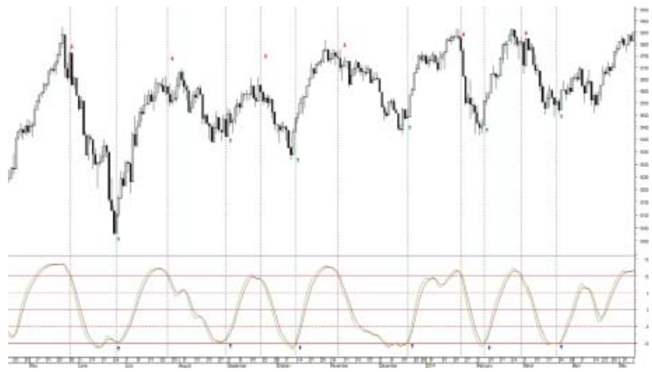
Overbought/Oversold:

We define the overbought area as anywhere above the 10 level. The oversold area is below -10. When the M-Oscillator goes above 10 (overbought) and then re-crosses it to the downside, a sell signal is triggered. When the M-Oscillator surpasses -10 to the downside and then re-crosses back above this level, a buy signal is triggered. This tactic is only successful during sideways markets; during an uptrend, the oscillator will remain in its overbought territory for long period of times. During a downtrend, it will remain in oversold for a long time.

Overbought/Oversold rule:

- **Buy** when the M-Oscillator violates the (-10) level to the downside and crosses back to the upside.
- **Sell** when the M-Oscillator crosses above the (+10) level and crosses back to the downside.

Figure 1. FTSE 100 INDEX — Daily Chart, from July 2013 to February 2014



Divergence

Divergence is one of the most striking features of the M-Oscillator. It is a very important aspect of technical analysis that enhances trading tactics enormously; it shows hidden weakness or strength in the market, which is not apparent in the price action. A positive divergence occurs when the price is declining and makes a lower low, while M-Oscillator witnesses a higher low. A negative divergence occurs when the price is rising and makes a higher High, while the M-Oscillator makes a lower high, which indicates hidden weakness in the market. Divergences are very important as they give us early hints of trend reversal (weekly chart)

Divergence rule:

- **Buy** when the M-Oscillator witnesses a positive divergence with prices followed by a rise above (-10).
- **Sell** when the M-Oscillator witnesses a negative divergence with prices followed by a decline below (+10).

Figure 2. NASDAQ INDEX — Daily Chart, from July 2015 to May 2016

Figure 3. EGX30 INDEX — Daily Chart, from May 2014 to June 2015

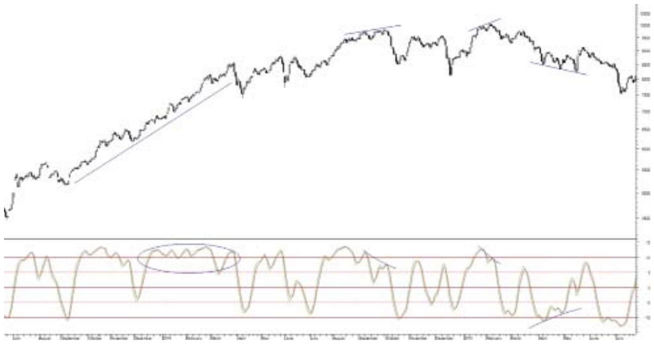
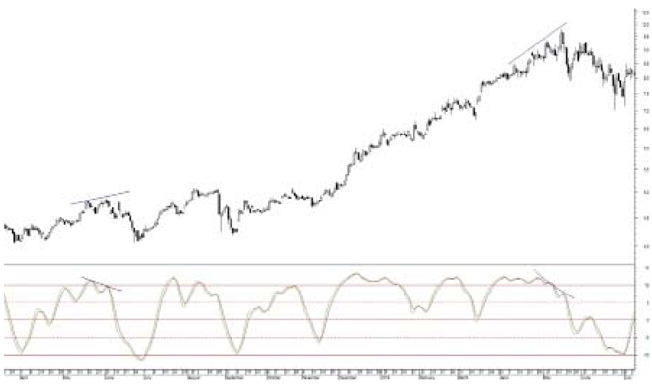


Figure 4. Emaar Properties — Daily Chart, from May 2013 to June 2014



Support and Resistance

During an uptrend, the M-Oscillator moves between (0) and (+10). During a downtrend, most of the time the M-Oscillator will move between (0) and (-10). Sometimes the (0) level acts as support (in the case of uptrends) and resistance (during downtrends). We can buy during an uptrend when the M-Oscillator reaches its midrange (0) and begins to move to the upside from there. During downtrends, an upward move to (0) might be a selling opportunity.

It is also used as exit signal (when the M-Oscillator acts as a resistance) as well as indication of a re-entry level (when the M-Oscillator acts as a support)

Exit signal:

When the M-Oscillator crosses above the (-10), giving a buy signal, but it doesn't retrace further than the zero line, the M-Oscillator drops towards the lower boundary. This is considered as weakness and an exit signal when the M-Oscillator drops from the zero line toward the (-10). (To avoid whipsaws, filters can be used.)

Figure 5. ADSMI — Daily Chart, from April 2008 to May 2009

Re-entry:

When the M-Oscillator breaks the (+10), giving a sell signal, but it doesn't retrace further than the zero line, the M-Oscillator rebounds toward the upper boundary. This is considered as strength and a re-entry point when the M-Oscillator rebounds from zero line to upside. (To avoid whipsaws, filters can be used.)

Figure 6. NIKKEI 225 Index — Daily Chart, from October 2012 to April 2013

Using M-Oscillator as a Trend Identifier on Long-Term Scale

During downtrends, the M-Oscillator does not reach overbought zone. A move toward the overbought area is a sign of strength when it occurs for the first time in a while. On the other hand, during uptrend, the M-Oscillator does not reach oversold areas easily. Going into oversold and staying there after a long time is a signal that the uptrend is reversing. (As Constance Brown explained in her book *Technical Analysis for the Trading Professional*, chapter 1, "oscillators do not travel between 0 and 100".)

Figure 7. SPX Index — Monthly Chart, from 1992 to 2010

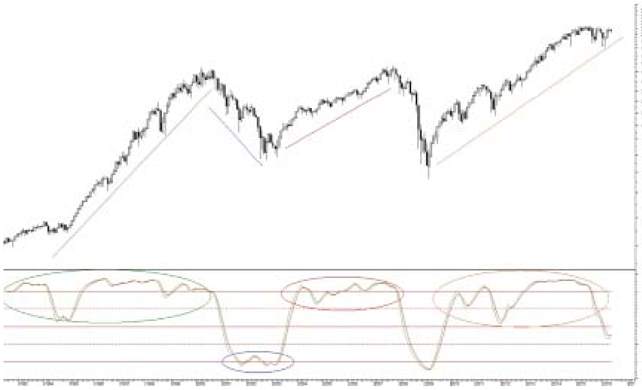
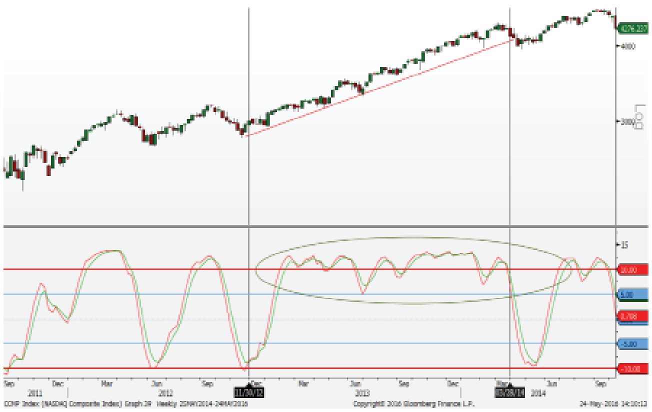


Figure 8. NASDAQ Index — Weekly Chart, from December 2011 to September 2014



Crossover on Extreme Levels

Sell signals are triggered when the M-Oscillator crosses its signal line above (13), which indicates an extreme market condition, and buy signals are triggered when the M-Oscillator crosses its signal line below (- 13)

Figure 9. DFMGI Index — Daily Chart, from September 2014 to February 2015

Results

Testing the M-Oscillator

Backtesting simulation control:

- Trading approach long only
- Initial capital 100K
- Default Trade Price current close

Uptrend

During uptrends, the buyers are controlling the markets, so it is very rare to see the MO in the oversold area, and we consider it as a very good opportunity (Add).

To define the uptrend in the Bloomberg system:

1. Buy when the MO crosses above (-10), and sell when the MO crosses below (10).
2. Buy when the MO rebounds from a level above (-10); buy signal triggered by crossing (-5) level to the upside, and sell signal triggered when (MO) crosses below its signal line below (5) level.
3. Stocks above their 60-day EMA are considered uptrend.

Table 2. Backtesting Result for 5 Years CAC Index (from 1/1/2012 to 1/1/2017)

Summary	
Trades	35
Wins	20
Losses	15
P&L	56.07K
%P&L	56.04%
Additional Stats	
Avg P&L	1.6K
Total Wins	101.47K
Total Losses	45.41K
Avg Win	5.07K
Avg Loss	2.03K
Max Win	21.57K
Max Loss	6.31
Num Bars	772
Avg Duration	22.06
Sharpe Ratio	0.88
Sortino Ratio	1.24
Total Return	56.07
% Max Return	56.07
% Min Return	-8.69
% Winning Ratio	57.14
% Losing Ratio	42.86

Figure 10. Backtesting Result for 5 years CAC 40 Index (from 1/1/2012 to 1/1/2017)

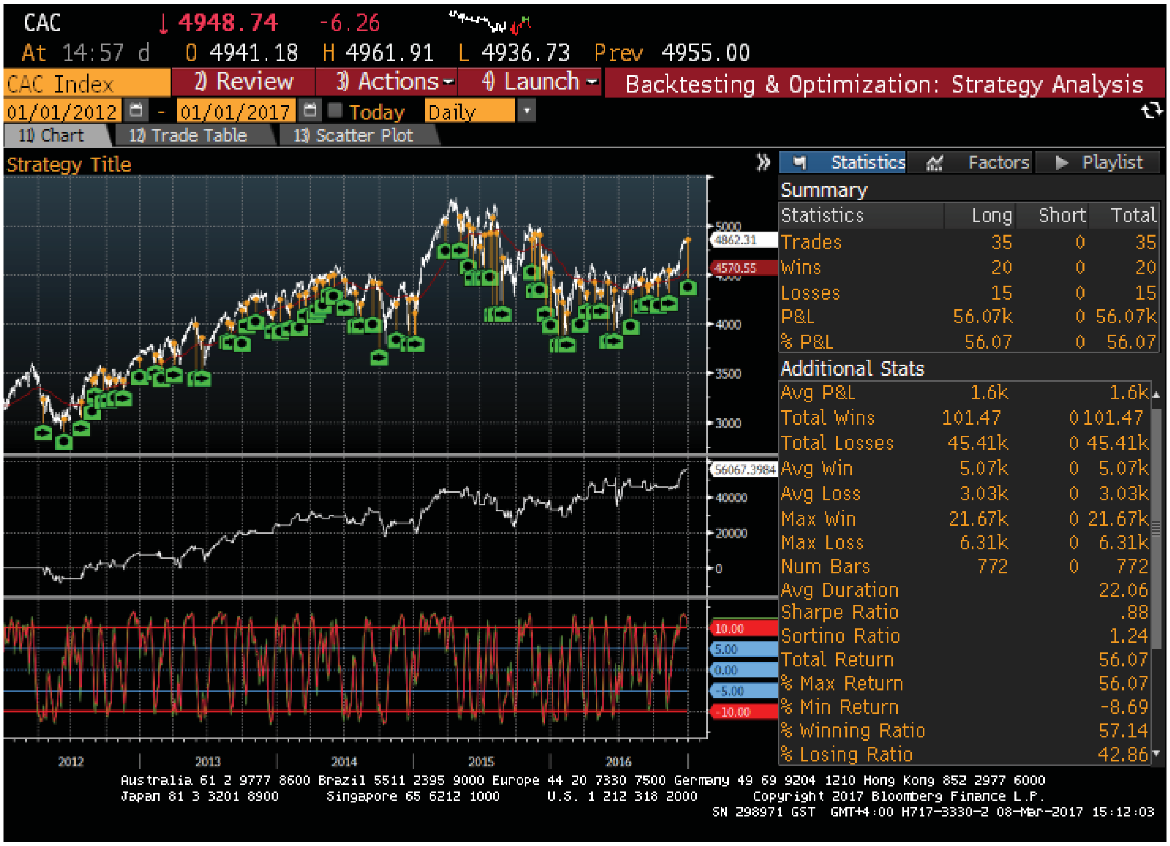


Figure 11. Backtesting Result for 5 Years CAC 40 Index (from 1/1/2012 to 1/1/2017

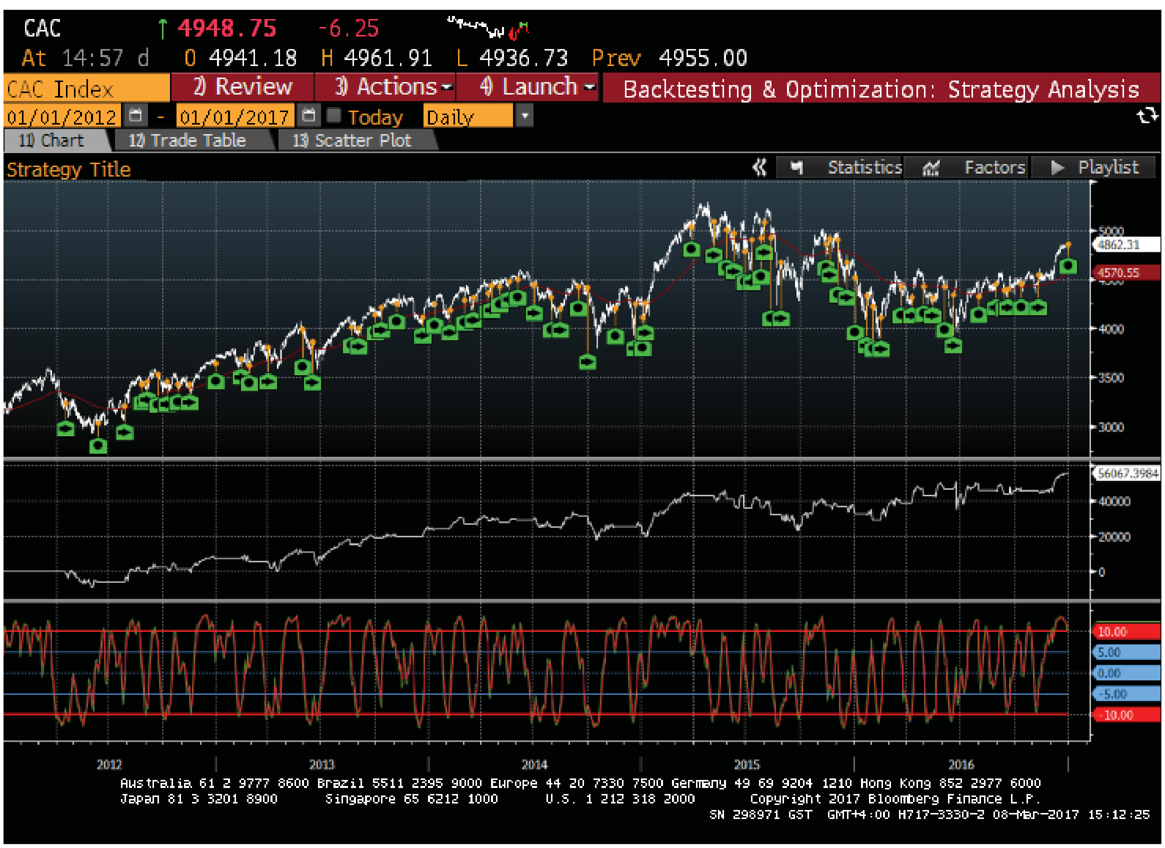


Table 3. Backtesting Result for 5 years DAX Index (from 1/1/2012 to 1/1/2017)

Summary	
Trades	34
Wins	18
Losses	16
P&L	34.07K
%P&L	34.07%
Additional Stats	
Avg P&L	1K
Total Wins	80.36K
Total Losses	46.29K
Avg Win	4.46K
Avg Loss	2.89K
Max Win	12.34K
Max Loss	7.16K
Num Bars	712
Avg Duration	20.94
Sharpe Ratio	0.63
Sortino Ratio	0.87
Total Return	34.07
% Max Return	34.07
% Min Return	-9.1
% Winning Ratio	52.94
% Losing Ratio	47.06

Figure 12. Backtesting Result for 5 Years DAX Index (from 1/1/2012 to 1/1/2017)

Figure 13. Backtesting Result for 5 years DAX Index (from 1/1/2012 to 1/1/2017)

Table 4. Backtesting Result for 5 Years NIKKEI 225 Index (from 1/1/2012 to 1/1/2017)

Summary	
Trades	29
Wins	17
Losses	12
P&L	62.36K
%P&L	62.36%
Additional Stats	
Avg P&L	2.15K
Total Wins	105.55K
Total Losses	43.19K
Avg Win	6.21K
Avg Loss	3.4K
Max Win	16.49K
Max Loss	17.74K
Num Bars	710
Avg Duration	24.48
Sharpe Ratio	0.92
Sortino Ratio	1.31
Total Return	62.36
% Max Return	65.16
% Min Return	-13.72
% Winning Ratio	58.62
% Losing Ratio	41.38

Figure 14. Backtesting Result for 5 Years NIKKEI 225 Index (from 1/1/2012 to 1/1/2017)

Figure 15. Backtesting Result for 5 Years NIKKEI 225 Index (from 1/1/2012 to 1/1/2017)

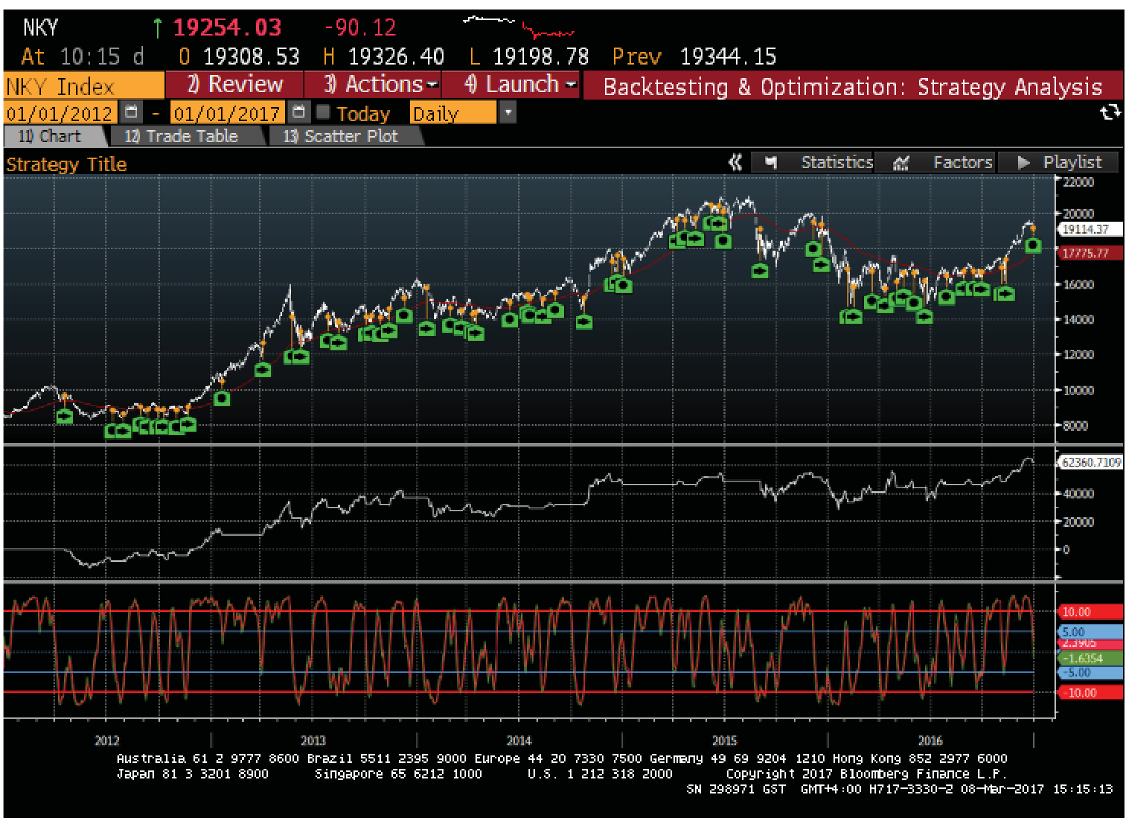


Table 5. Backtesting Result for 5 Years INDU Index (from 1/1/2012 to 1/1/2017)

Summary	
Trades	39
Wins	20
Losses	19
P&L	47.05K
%P&L	47.05%
Additional Stats	
Avg P&L	1.21K
Total Wins	74.85K
Total Losses	27.8K
Avg Win	3.74K
Avg Loss	1.46K
Max Win	10.92K
Max Loss	8.99K
Num Bars	782
Avg Duration	20.05
Sharpe Ratio	1.17
Sortino Ratio	1.6
Total Return	47.05
% Max Return	48.13
% Min Return	-6.28
% Winning Ratio	51.28
% Losing Ratio	47.72

Figure 16. Backtesting Result for 5 Years INDU Index (from 1/1/2012 to 1/1/2017)

Figure 17. Backtesting Result for 5 Years INDU Index (from 1/1/2012 to 1/1/2017)

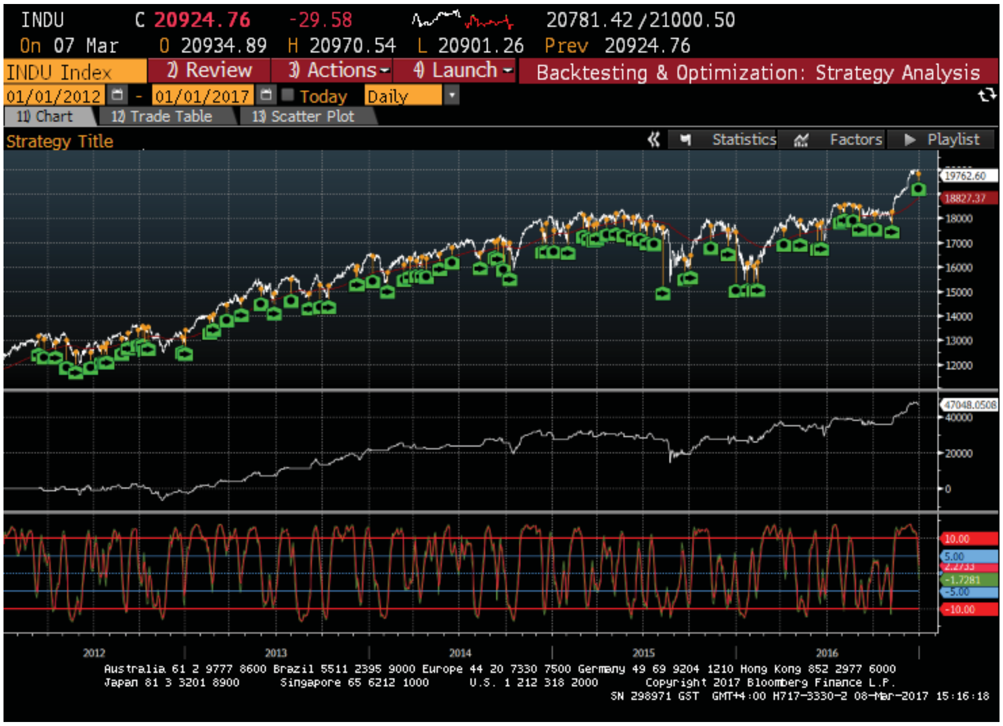


Table 6. Backtesting Result for 5 Years Facebook Index (from 1/1/2012 to 1/1/2017)

Summary	
Trades	33
Wins	22
Losses	11
P&L	194.09K
%P&L	194.09%
Additional Stats	
Avg P&L	5.88K
Total Wins	292.5K
Total Losses	98.4K
Avg Win	13.3K
Avg Loss	8.95K
Max Win	56.52K
Max Loss	34.22K
Num Bars	618
Avg Duration	18.73
Sharpe Ratio	1.3
Sortino Ratio	2.35
Total Return	194.09
% Max Return	211.65
% Min Return	-30.42
% Winning Ratio	66.67
% Losing Ratio	33.33

Figure 18. Backtesting Result for 5 Years Facebook (from 1/1/2012 to 1/1/2017)

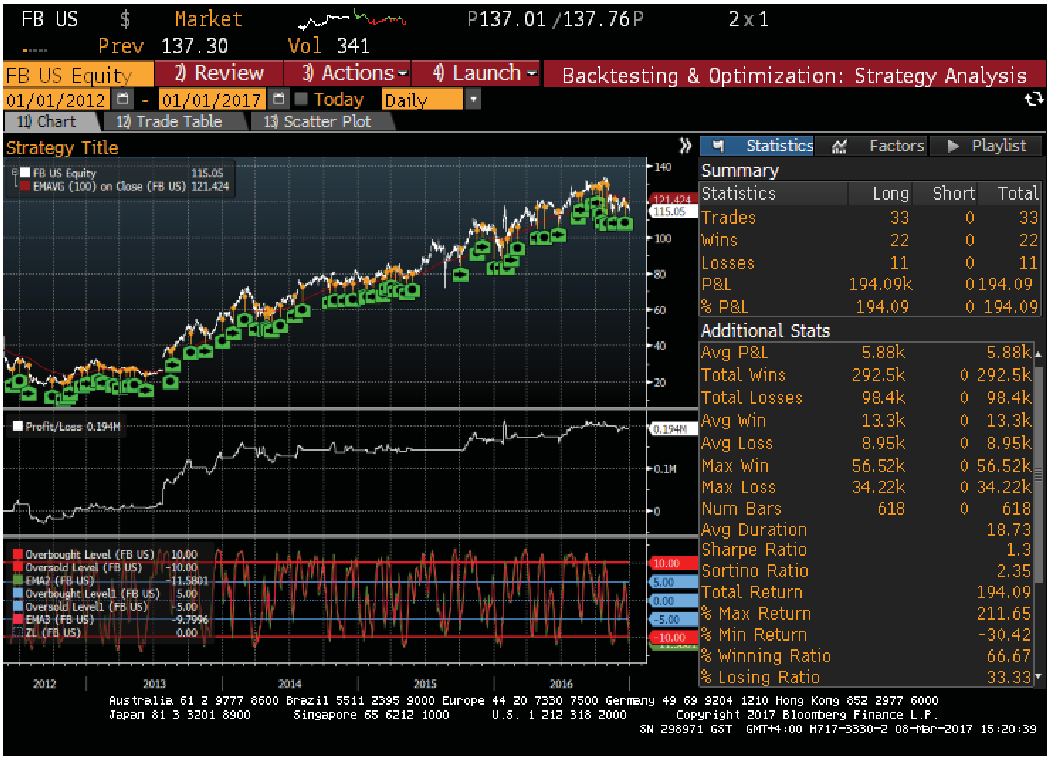


Figure 19. Backtesting Result for 5 Years Facebook (from 1/1/2012 to 1/1/2017

Table 7. Backtesting Result for 5 Years NFLX Index (from 1/1/2012 to 1/1/2017)

Summary	
Trades	27
Wins	20
Losses	7
P&L	251.33K
%P&L	251.33%
Additional Stats	
Avg P&L	9.31K
Total Wins	468.75K
Total Losses	217.42K
Avg Win	23.41K
Avg Loss	31.06K
Max Win	78.96K
Max Loss	80.61K
Num Bars	728
Avg Duration	26.96
Sharpe Ratio	1.27
Sortino Ratio	2.2
Total Return	251.33
% Max Return	387.91
% Min Return	-22.14
% Winning Ratio	74.07
% Losing Ratio	25.93

Figure 20. Backtesting Result for 5 Years NFLX (from 1/1/2012 to 1/1/2017)

Figure 21. Backtesting Result for 5 Years NFLX (from 1/1/2012 to 1/1/2017)

Downtrend

During downtrends, the sellers are controlling the markets, so it is very rare to see the M-Oscillator in the overbought area, and we consider it as a very good opportunity to sell.

To define the downtrend in the Bloomberg system:

1. Sell when the MO crosses below (10), and buy when MO crosses above (-10).
2. Sell when the MO rebounds from a level below (10); sell signal triggered by crossing (5) level to the downside.
3. Stocks below their 60-day EMA are considered downtrend.

Table 8. Backtesting Result for 5 Years EUR CURNCY (from 1/1/2012 to 1/1/2017)

Summary	
Trades	20
Wins	13
Losses	7
P&L	5.53K
%P&L	5.53%
Additional Stats	
Avg P&L	276.67
Total Wins	15.36K
Total Losses	9.83K
Avg Win	1.18K
Avg Loss	1.4K
Max Win	2.78K
Max Loss	5.72K
Num Bars	224
Avg Duration	11.2
Sharpe Ratio	0.28
Sortino Ratio	0.41
Total Return	5.53
% Max Return	6.74
% Min Return	-3.69
% Winning Ratio	65
% Losing Ratio	35

Figure 22. Backtesting Result for 5 Years EUR CURNCY (from 1/1/2012 to 1/1/2017)

Figure 23. Backtesting Result for 5 Years EUR CURNCY (from 1/1/2012 to 1/1/2017)

Table 9. Backtesting Result for 5 Years Gold (from 1/1/2012 to 1/1/2017)

Summary	
Trades	21
Wins	14
Losses	7
P&L	27.97K
%P&L	27.97%
Additional Stats	
Avg P&L	1.33K
Total Wins	39.12K
Total Losses	11.15K
Avg Win	2.79K
Avg Loss	1.59K
Max Win	6.93K
Max Loss	5.04K
Num Bars	258
Avg Duration	12.29
Sharpe Ratio	0.88
Sortino Ratio	1.32
Total Return	27.97
% Max Return	29.16
% Min Return	-4.79
% Winning Ratio	66.67
% Losing Ratio	33.33

Figure 24. Backtesting Result for 5 Years Gold (from 1/1/2012 to 1/1/2017)

Figure 25. Backtesting Result for 5 Years Gold (from 1/1/2012 to 1/1/2017)

Sideways

During a sideways period, sellers and buyers are equal.

To define a sideways period in the Bloomberg system:

1. Buy when the M-Oscillator crosses above (-10), and sell when the M-Oscillator crosses below (10).
2. When buyers and sellers show some strength to the upside or downside, we consider the buying signal when the MO breaks above (-5) and the sell signal when it breaks (5) to the downside.
3. ADX (14) below (25) is considered a sideways.

Table 10. Backtesting Result for 5 Years CAC Index (from 1/1/2012 to 1/1/2017)

Summary	
Trades	15
Wins	9
Losses	6
P&L	24.01K
%P&L	24.01%
Additional Stats	
Avg P&L	1.6K
Total Wins	36.75K
Total Losses	12.74K
Avg Win	4.08K
Avg Loss	2.12K
Max Win	7.99K
Max Loss	7.26K
Num Bars	449
Avg Duration	29.93
Sharpe Ratio	0.51
Sortino Ratio	0.69
Total Return	24.01
% Max Return	26.78
% Min Return	-5.16
% Winning Ratio	60
% Losing Ratio	40

Figure 26. Backtesting Result for 5 Years CAC 40 Index (from 1/1/2012 to 1/1/2017)

Figure 27. Backtesting Result for 5 Years CAC 40 Index (from 1/1/2012 to 1/1/2017)

Table 11. Backtesting Result for 5 Years DAX Index (from 1/1/2012 to 1/1/2017)

Summary	
Trades	15
Wins	10
Losses	5
P&L	11.52K
%P&L	11.52%
Additional Stats	
Avg P&L	768.05
Total Wins	41.7K
Total Losses	30.17K
Avg Win	4.17K
Avg Loss	6.03K
Max Win	8.25K
Max Loss	15.6K
Num Bars	615
Avg Duration	41
Sharpe Ratio	0.26
Sortino Ratio	0.36
Total Return	11.52
% Max Return	13.63
% Min Return	-15.36
% Winning Ratio	66.67
% Losing Ratio	33.33

Figure 28. Backtesting Result for 5 years DAX Index (from 1/1/2012 to 1/1/2017)

Figure 29. Backtesting Result for 5 Years DAX Index (from 1/1/2012 to 1/1/2017)

Table 12. Backtesting Result for 5 Years NIKKEI 225 Index (from 1/1/2012 to 1/1/2017)

Summary	
Trades	17
Wins	11
Losses	6
P&L	2.92K
%P&L	2.92%
Additional Stats	
Avg P&L	171.58
Total Wins	25.88K
Total Losses	22.96K
Avg Win	2.35K
Avg Loss	3.83K
Max Win	7.86K
Max Loss	12.51K
Num Bars	378
Avg Duration	22.24
Sharpe Ratio	0.11
Sortino Ratio	0.16
Total Return	2.92
% Max Return	8.65
% Min Return	-17.75
% Winning Ratio	64.71
% Losing Ratio	35.29

Figure 30. Backtesting Result for 5 Years NIKKEI 225 Index (from 1/1/2012 to 1/1/2017)

Figure 31. Backtesting Result for 5 Years NIKKEI 225 Index (from 1/1/2012 to 1/1/2017)

Discussion

In this section, there will be discussion about the advantages and disadvantages of the M-Oscillator.

Advantages

- One of the most important features of the M-Oscillator is that it relieves the volatility of the price movements (i.e., reacts to the changes in price regardless of the magnitude).
- It can measure the strength and the direction of the market trend.
- The M-Oscillator considers the flat movements between two closing prices as zero. An important outcome was noticed that a flat movement between two closing prices is rarely witnessed, but it is very important when using a small timeframe (intraday charts), as it gives an accurate trading signal.
- Using trendlines, chart patterns and channels has significant value.

Disadvantages

- The M-Oscillator does not provide a price target.

The M-Oscillator vs. Trendscore

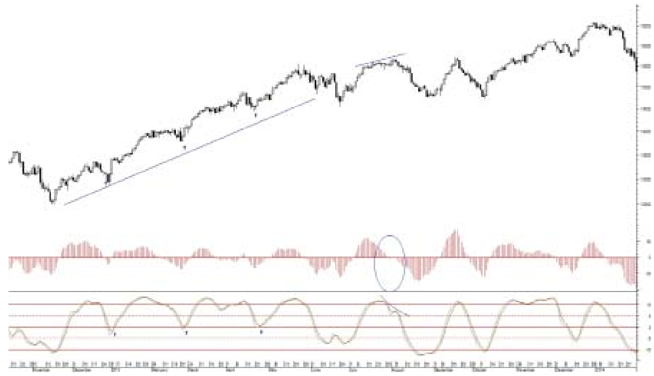
This section compares the M-Oscillator vs. trendscore; the comparison will be on the basic points, including the method of the calculation.

- The calculations of the trendscore starts at 11 days back from the present and goes back another 10 days, where the M-Oscillator starts at the present and goes 14 days back, so the trendscore is ignoring the recent data, while the M-Oscillator is the summation of the 14-day momentum, which takes the advantages of the momentum and ignores the disadvantages (discussed previously).
- Minor market correction is enough to send the trendscore down to -10, which is referred to as downward. The M-Oscillator is double smoothed, and add to that the fact that in the sharp moves to the upside, the M-Oscillator fluctuates between 5 and 14, and during sharp down moves, it fluctuates between -5 and -14.
- Within the calculation process, the trendscore ignores the flat move between any two closing values and considers it as an up move, while the M-Oscillator interprets two consecutive closing prices as a zero value, which is very important when used for intraday trading.
- Trendscore does not work properly in the intraday time frame 5M, 30M, and hourly, etc.
- Trendscore does not support divergence analysis.

M-Oscillator vs. MACD-Histogram

One of the strongest signals in technical analysis divergences occurs between MACD-Histogram and prices. These signals rarely occur, but when they do, they often let you catch major reversals and beginnings of new trends (Alexander Elder). As shown on the chart below, the divergence was very clear with the M-Oscillator, while MACD-histogram didn't react to this signal.

Figure 32. INDU Index — Daily Chart, from March to December 2013



M-Oscillator (MO) With Normalized Relative Performance Oscillator (NRPO)

Normalized Relative performance (NRP) is one of the most valuable tools in technical analysis. It measures the performance of a specific security relative to another. The NRP calculation is very simple:

$$\text{NRP} = \frac{\text{Security's close (today)}}{\text{Security's Reference close (at N)}} \div \frac{\text{Benchmark's close (today)}}{\text{Benchmark's Reference close (at N)}}$$

This means that if the curve is rising, then the nominator is rising in a faster way than the denominator, or the denominator is falling in a faster way than the nominator; in both ways, the security is outperforming its benchmark.

One of the drawbacks the NRP is that it is plotted as a line chart, which describes the limitation of data it provides. Add to that the need to have a complete line chart curve to know which security is outperforming the other, it is considered very late in terms of making an investment decision.

The best way to benefit from relative performance (RP) is to convert the RP line to be an Relative Performance Oscillator (RPO) by applying the same methodology used for calculating the M-Oscillator (explained).

NRPO Calculation

1. We calculate the NRP of the underlying security with its benchmark.
2. Apply the same formula used for M-Oscillator to convert the RP line chart to be an oscillator.

NRPO Interpretations and Benefits

- Does not give buy/sell signals; it gives a clear view about the entity that will outperform its benchmark.
- Constructed daily and can be converted to weekly, monthly or any time frame, even intraday.
- Bounded between +14 and -14.
- A security signals outperformance when NRPO crosses (-5) level to upside and signals underperformance when it cross (+5) to downside.

Figure 33. Weekly Chart Apple vs. S&P 500

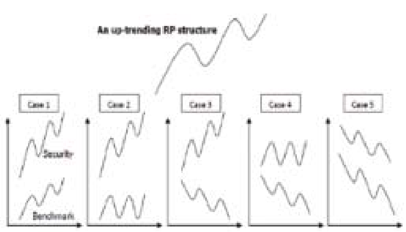
- From October 2012 until August 2013, APPLE was underperforming the S&P 500.
- An underperformance signal was triggered when the NRPO crossed +5 to downside
- The result:

	5th October 2012	2nd August 2013	performance
APPLE	93.23	66.08	-29.12%
SP500	1460.93	1709.67	17.03%

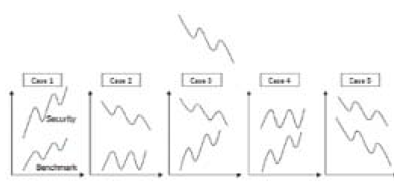
Combined M-Oscillator With Normalized Relative Performance Oscillator (NRPO)

Since NRPO gives signals for outperformance and underperformance, there are three main outcomes:

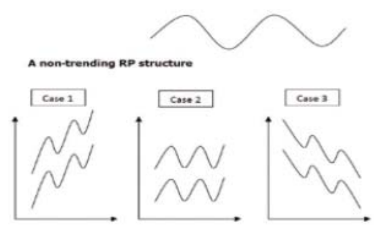
1. An uptrend (5 cases)



2. A downtrend (5 cases)



3. A non-trending (3 cases)



The way to get ultimate benefit out of NRPO and reduce the number of outcomes is to combine the NRPO with the M-Oscillator and choose the cases when the security is up (getting buy signal from the M-Oscillator) and the NRPO is crossing (-5) to upside (outperforming).

Signal (case 1): Buy when both the M-Oscillator and NRPO cross (-5) to upside and sell when they cross (+5) to downside.

Figure 34. Dubai Investment (DIC) vs. Dubai Financial Market (DFMGI)

	5th Feb 2015	18th June 2015	performance
DIC	2.38	2.86	**20.17%**
DFMGI	3886.53	4063.88	**4.56%**

Figure 35. Emirates Integrated Telecommunications (DU) vs. Dubai Financial Market (DFMGI)

	24th Dec 2015	12th May 2016	performance
DIC	5.07	6.39	**26.04%**
DFMGI	3137.32	3344.67	**6.61%**

Conclusion

M-Oscillator is constructed by applying principles of the momentum oscillator. M-Oscillator aims to fix the problems associated with the momentum oscillator, such as absence of boundaries (overbought and oversold) and disproportionate moves in the momentum line vis-à-vis prices.

M-Oscillator is a leading oscillator useful in generating buy/sell signals in advance, spotting divergences, and identifying overbought /oversold areas. It also provides guidance regarding re-entry and position upsizing. It is a handy tool for trend identification and for measuring strength of the trend.

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Software and Data

Bloomberg (www.bloomberg.com)

Metastock XENITH (www.Metastock.com)

MS-Excel (www.microsoft.com)

Is There Smart Beta in Indicators of Technical Analysis?

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Abstract

The aim of this thesis was to investigate empirically whether higher systematic risk-adjusted returns can be obtained using indicators from technical analysis compared to the ones obtained from the S&P 500 and S&P 500 monthly equally weighted indices. Smart beta strategies, which are rule-based and transparent, provided a framework for the investigation. At present, however, they are executed in the markets based only on factors obtained by fundamental analysis.

The investigation was carried out by selecting factors retrieved from 10 technical analysis indicators. Based on these, an equally weighted factor portfolio was built on a monthly basis containing, according to the indicators, the 100 most attractive equities out of the S&P 500 investment universe. Furthermore, one- and two-dimensional key figures, sustainability tests, and statistical quantities were investigated over a time horizon of 20 years, including different market cycles.

The results show that systematic, risk-adjusted returns were possible using technical indicators. Overall, nine out of 10 obtained better returns compared to the S&P 500. Compared to the monthly equally weighted S&P 500, five out of 10 obtained better returns. Assessing the selection ability revealed, however, that some of the overperformance was due to the equally weighted portfolio. This thesis is of interest for technical analysts, quantitative researchers and the ETF industry.

Introduction

Establishment of smart beta

According to the study "EY Global ETF Survey 2015" by Ernst & Young regarding the global ETF market, the ETF industry was able to expand and generate "Assets under Management".[1] Substential inflow of funds were also recorded in the branch of smart beta. Within only 10 years, their assets on a global scale increased exponentially from a one-digit billion figure to USD $382 billion. According to ETFGI, 764 smart beta equity ETFs/ETPs exist globally, offered by 106 issuers in 27 countries.[2]

Smart beta has become a vogue expression. The concept has its roots in the 1970s,[3] with the development of the Capital Asset Pricing Model (CAPM). CAPM separates the active return of a strategy compared to a benchmark into two components: Beta, containing the part coming from the returns depending on the benchmark, and alpha, containing the remainder of the returns being explained by the "active deviation of the strategy" compared to the benchmark.

Advanced work by Fama/French and Carhart explain alpha in more detail using factors like value, small-cap, momentum and low-volatility.

This finding is presently mainly used by institutional investors to integrate factor premiums and risks in their investment processes. This trend was subesquantly taken up by ETF providers and asset managers that sucessfully launched smart beta strategies.

Meanwhile, the label smart beta has been established. However, a number of synonyms were introduced, such as strategic beta, enhanced beta, factor investing and style investing. At present, they are mostly applied to equities.

More important than semantics is to differentiate according to which criterion or criteria the portfolio or index is constructed of. These criteria are subsequently referred to as factors. They should be transparent and implemented in a rule-based fashion.

Factors are in essence nothing but quantifiable properties of equities,[4] for example, the factor "small size". This specific factor aims at selecting equities bearing the lowest market capitalization in an investment universe. In a uniform manner, identified equities are then selected in periodically occurring intervals to form a portfolio.

By introducing new smart beta strategies, providers often do not aim at generating approved risk premiums. Instead, they aim at systematic equity selection using one ore more factors to offer better risk-adjusted returns. These factors are at present based on fundamental analysis (FA) only. In-depth theories and strategies based on technical analysis (TA) are to the author's knowledge not yet published.

Aim of this thesis

The aim of this thesis is to find out whether indicators from technical analysis offer a foundation for smart beta strategies and surplus value. It is investigated whether in the equity market of the United States of America, represented by the investment universe of the S&P 500, systematic, risk adjusted returns could be obtained using factors from TA. The time period of the investigation is from 1995 to 2015. It is further assessed whether higher risk-adjusted returns appear in a random or constant manner.

In the first step, 10 different indicators from TA are introduced that will serve as factors. In the second step, the obtained results are presented in key figures and graphical comparisons. It will be determined whether a surplus value compared to the benchmarks is obtained over the observation period of 20 years. Therefore, one- and two-dimensional key figures are computed. The key figures will further be compared in four different market cycles and two bear market phases to understand their behavior in different environments. In the third step, the rolling correlation and rolling beta compared to the S&P 500 are analyzed over the total observation period and the different market cycles. In the fourth step, it is investigated whether, besides "smart equities", "stupid equities" are also found in the investment universe. In the fifth step, statistical tests and quantities are analyzed to test the robustness of the results. Finally, a summary is given on which factors sustainably carry systematic, risk-adjusted returns and what applications exist in practice.

Material and Methods

Technical indicators and their role as factors

In principal, factors of smart beta strategies should have the following properties:

- Based on objective rules
- Transparent
- High capacity
- Capture well-understood drivers of returns

Indicators of TA are objective, transparent and scalable, as they are based on mathematical or statistical computations taking time series of prices and/or volume as input.[5] An economical foundation is not fulfilled. As an example, recall the factor "size", which assumes that small cap equities develop better than large cap equities since they bear greater risk.[6] This kind of reasoning is not explained by TA factors. Rather, they are explained by the philosophy of TA and behavioral finance, which are, however, not a component of this thesis.

In this thesis, different TA factors are tested. Oscillators, a subset of technical indicators, take values between 0 and 100, whereas the value of the remaining ones have no theoretical boundary. The time scale for seven of 10 technical indicators is set to be 30 periods. The technical indicators MACD, Stochastic and REX include, among others, signal lines, which are computed on shorter time scales. Since the investment universe is analyzed on a monthly basis, these choices appear harmonic and are chosen with discretion. To form a strong framework for the investigations, 10 different[7] indicators, subsequently referred to as factors, are investigated separately.

1. RSI — Relative Strength Index, developed by Welles Wilder Jr., is an oscillator indicating "overbaught" and oversold" conditions.
2. DMI — Directional Movement Index; developed by Welles Wilder Jr., is an indicator to determine the strength of a trend.
3. MACD — Moving Average Convergence Divergence, developed by Gerald Appel, is a trend-following indicator also displaying the strength of a trend.
4. ROC — Rate of Change, is an oscillator measuring velocity and strength of a price movement.
5. Bollinger Bands, developed by John Bollinger, are an indicator having its foundation on a moving average (middle band), displaying the trend. The middle band is supplemented by two further bands (upper and lower band), which are computed by the standard deviation of the middle band.
6. CCI — Commodity Channel Index, developed by Donald Lambert, is a trend-following indicator computing the deviation from the statistical mean.
7. Stochastic, developed by George C. Lane, is an oscillator. It is formed by exponential averages taking into account the difference between closing price and the low of a period.
8. ATR — Average True Range, developed by Welles Wilder, is an indicator displaying volatility by the mean-difference of high and low prices.
9. Hurst Exponent, having its roots in fractal geometry and chaos therory, is a an oscillator estimating the presence of a trend or random process.
10. Rex Oscillator[8] is an oscillator displaying in a bar the relation between closing and opening price.

During the selection process of the indicators, care was taken to choose them such that they do not bear a strong correlation among themselves, especially synchronization.

Investment universe and factor portfolio

The investment universe is assumed to be represented by the S&P 500 index given by its 500 constituent stocks. For each of its index members, the factor (indicator) is computed on a monthly basis and sorted from its lowest to highest factor score. The factor score represents the value of each indicator applied to each respective equity. Whether a high factor score is attractive or unattractive was determined by a preceding analysis. For all 10 factors, a low value stands for attractiveness while a high value stands for unattractiveness. Therefore, it does not matter how the indicator is interpreted in the literature.

Subsequently, a division in five segments is made (i.e., five quantiles, each bearing the same probability frequency). Out of the first quantile, a factor portfolio is constructed, which is supposed to represent the factor itself. It is generally formed of 20% of the index members (i.e., 100 stocks, which are each equally weighted). The construction process is repeated each month, meaning the factor portfolio is time-variant and periodically rebalanced.

The benchmarks

To assess the results of the factors, a comparison against two benchmarks is made. The first benchmark is the S&P 500 as total return index. Standard and Poor´s 500 index is a capitalization-weighted index of 500 stocks.

Since the respective factor portfolio is equally weighted, a second benchmark is introduced, namely the investment universe S&P 500 equally weighted. The index includes the same constituents as the capitalization weighted S&P 500, but each company in the S&P 500 EQW is allocated a fixed weight of the index total at each monthly rebalance.

Market cycles

To analyze the advantages and disadvantages of the factors relative to their benchmarks, a backtest from 1995 to 2015 is made. This time period includes different market and economy cycles (e.g., the New Economy/Dotcom bubble, the financial crisis). Additionally, the whole time period is divided into four different market cycles. To analyze a whole market cycle, high to market high and low to market low cycles are analyzed as well as two bear markets.

Remarks regarding the backtest

The database comes from Bloomberg offering historic point-in-time data. This means the tests are carried out based on index members at distinct given times. Hence, "survivorship" or "lagging bias"[10] are avoided. Adjusted prices and dividends are considered, whereas transaction costs are not. Maximum drawdown and volatility are computed from daily data. The parameters of the technical indicators and of how many stocks the factor portfolio is constructed of is chosen arbitrarily since no right or wrong for the choices exists.

Results

One-dimensional key figures

To assess the investment success over the whole time period, the one-dimensional key figures "total return" (indexed) and "annualized return" are computed to measure performance. The quantities "volatility" and "maximum drawdown" are computed to measure risk.

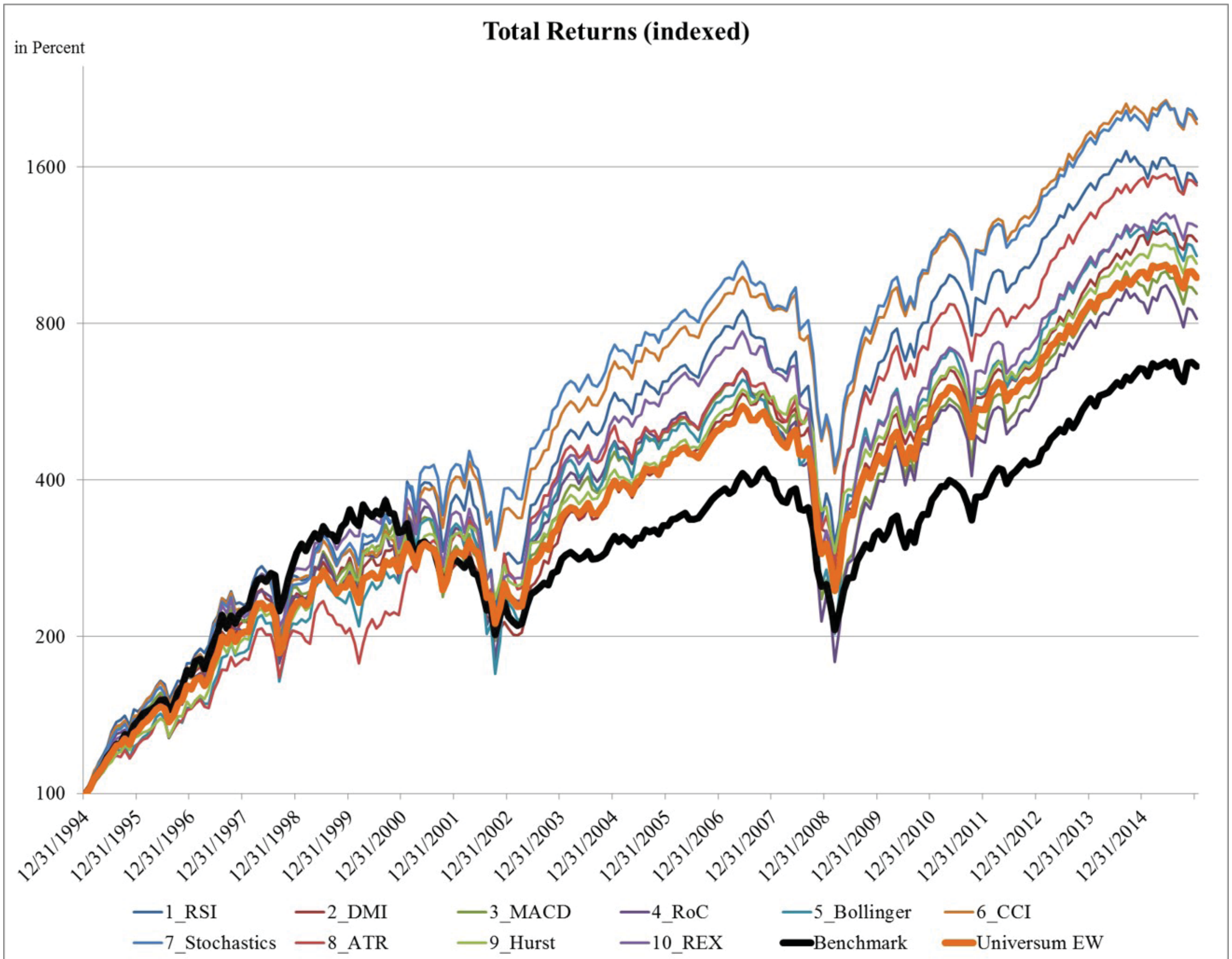
Outperformance of all factors compared to the S&P 500

In the defined investment universe, all 10 investigated factors based on technical analysis indicators, from 1995 to 2015, showed an outperformance compared to the capitalization-weighted S&P 500. Indexed and starting from 100, the S&P 500 achieved 662% while the S&P 500 EQW achieved 981%. This was outperformed by eight of 10 factors.

Table 1. Overview of market cycles and methods of analysis

				will be examied						
				one-dimensional measures		two-dimensional				
Market Cycle	Start Date	End Date	Complete Market Cycle in Weeks	Performance Analysis	Risk Analysis	Risk-Adjusted Performance	Analysis of Correlation	Analysis of Beta	Analysis of Qspread	Analysis of Statistics
Total Cycle	01/01/1995	12/31/2015	1095	✔	✔	✔	✔	✔	✔	✔
Market Cycle 1	01/01/1995	04/10/2002	405	✔	✔	✔	✔	✔	x	x
Market Cycle 2	08/09/2000	05/10/2007	370	✔	✔	✔	✔	✔	x	x
Market Cycle 3	04/10/2002	02/27/2009	355	✔	✔	✔	✔	✔	x	x
Market Cycle 4	05/10/2007	12/31/2015	429	✔	✔	✔	✔	✔	x	x
DrawDown Cycle I	01/09/2000	04/10/2002	109	x	x	x	✔	✔	x	x
DrawDown Cycle II	05/10/2007	06/03/2009	74	x	x	x	✔	✔	x	x

Figure 1. Indexed returns of factors vs. S&P 500 and S&P 500 EQW



The results for the factors Stochastics and CCI are notably better than for the S&P 500 EQW. RSI, ATX and REW are located between 1200% and 1500%; all remaining factors performed below. Only MACD and Hurst Exponent are positioned below the performance of the S&P 500 EQW.

Figure 1 shows that the factors' outperformance is mainly built during several years of uptrending phases. Further, a diverging development for some factors during the period from August 2000 to March 2003 is noted. For example, Stochastics shows new highs while the benchmarks move sideways. Furthermore, higher volatility and drawdowns are present during several years of downtrends. These visual findings are reviewed in the following key figures.

All annualized returns obtained by the 10 factors are located above the one of the S&P 500 being 9.4%. Eight factors are better than the S&P 500 EQW, which, with 11.5%, has a higher return than the S&P 500. Significantly above are the annualized returns of the factors RSI with 13.7%, CCI with 15.1% and Stochastics with 15.3%.

Volatility

One risk measure is volatility. This quantity computes the fluctuation around the mean value. The higher this fluctuation, the more volatile, hence riskier, the factor is. Compared to the S&P 500, whose volatility is 19.5%, only four factors show a lower volatility. The volatility of the S&P 500 EQW is 17%. Out of the 10 considered factors, only DMI appears to have a lower value.

Maximum drawdown

As also shown in Figure 1, the drawdowns of the factors are higher than those of the S&P 500. The maximum drawdown quantifies the maximum cumulated loss in percent during a considered period. The S&P 500 shows a maximum drawdown of -55%; all 10 factors are worse. Also, the S&P 500 EQW performs worse, with a maximum drawdown of -60%. Overall, eight factors appear worse.

Figure 2. Volatility of factors vs. S&P 500 and S&P 500 EQW

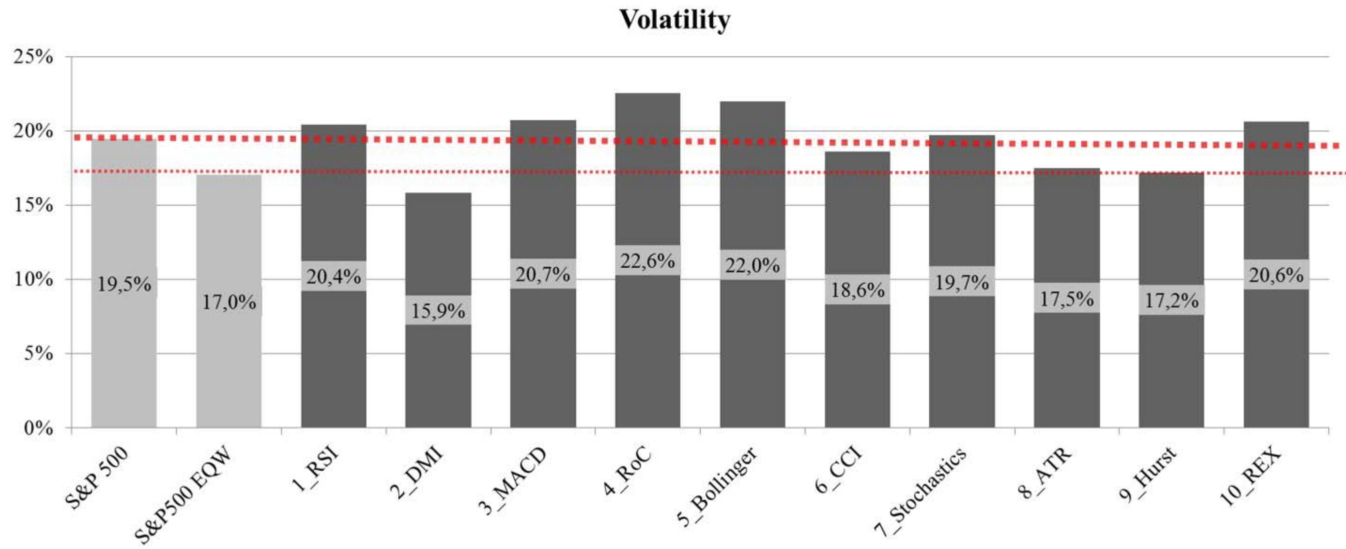
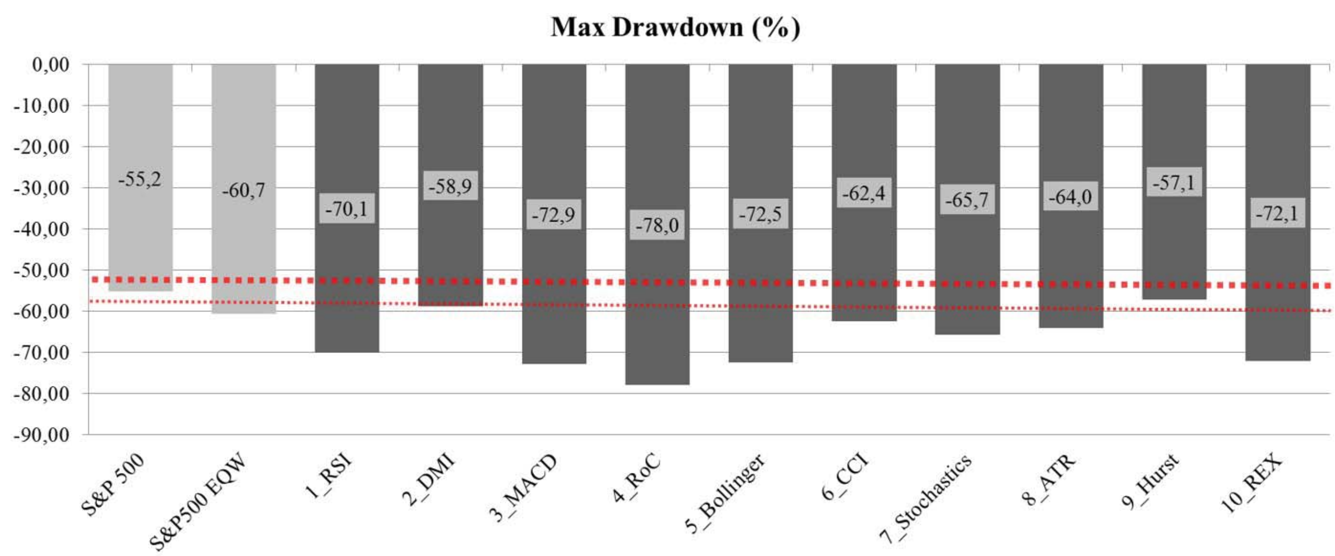


Figure 3. Maximum drawdown of factors vs. S&P 500 and S&P 500 EQW



Remarkable are the negative results for the factors RSI, MACD, RoC, Bollinger Bands and REX, which appear to have 10% higher drawdowns than the S&P 500 EQW.

Two-dimensional key figures

Two-dimensional key figures are understood to be risk-adjusted measures.[11] They shall show in the following whether the predominantly higher risks of the respective factors can be compensated by their significant outperformance in returns.

Sharpe Ratio

The Sharpe Ratio shows how annualized returns relate relative to taken risks, measured in volatility.[12] The higher the Sharpe Ratio, the better. Although the volatility of the factors are higher on average, nine of 10 factors have a higher Sharpe Ratio than the S&P 500. Only RoC shows a lower Sharpe Ratio than the S&P 500, wheareas one factor shows the same as the S&P 500 EQW. Four factors have a significantly higher one. The assumed risk-free rate to calculate the Sharpe Ratio is 0%.

Figure 4. Sharpe ratio of factors vs. S&P 500 and S&P 500 EQW

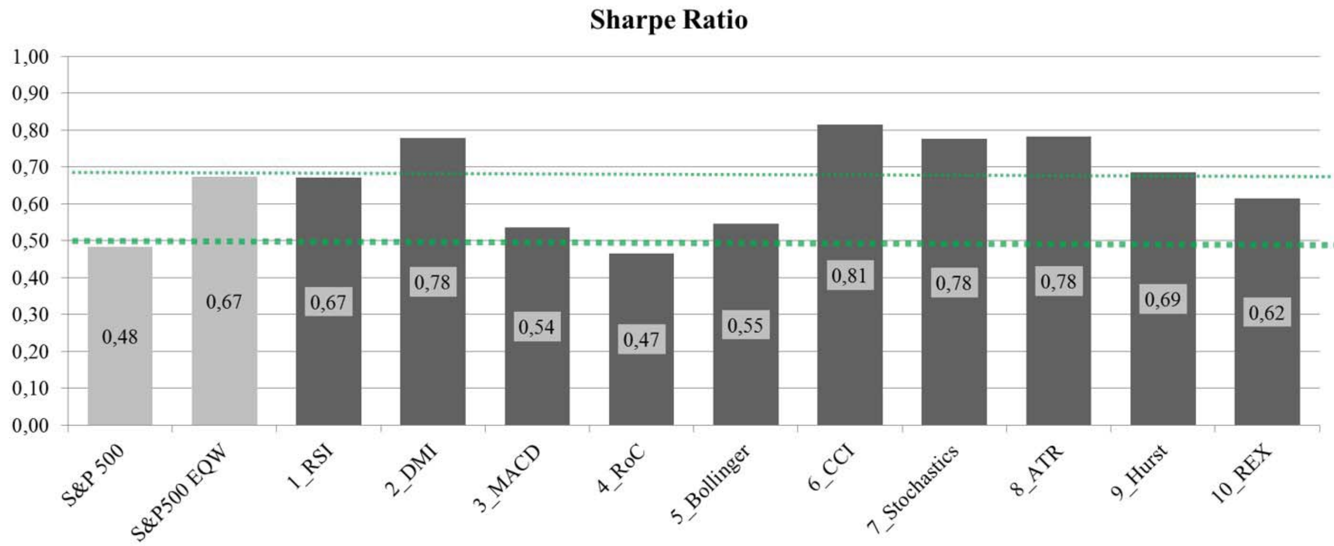
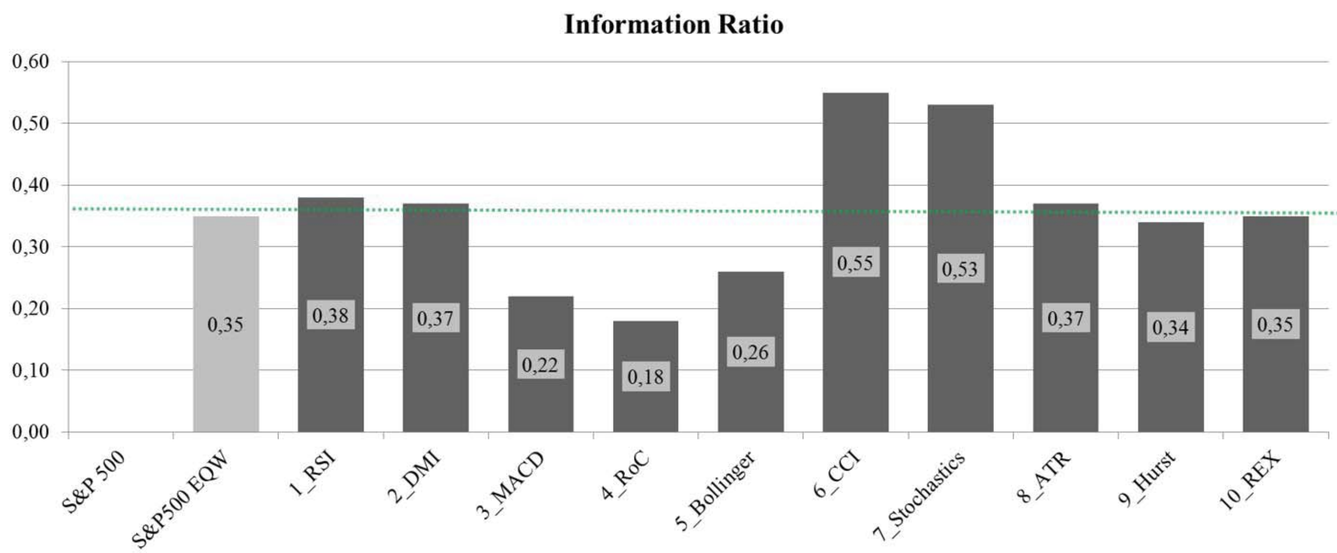


Figure 5. Information ratio of factors vs. S&P 500 & S&P 500 EQW



Information Ratio

Information Ratio[13] gives an indication whether a factor outperformes[14] the S&P 500 by its active deviations and is further a measure about consistency of relative performance. The higher the ratio, the higher the information advantage.

Values above zero indicate outperformance to be expected. All 10 factors show a positive information ratio compared to the S&P 500. The S&P 500 EQW shows a value of 0.35. MACD, RoC and Bollinger are on a satisfying level. RSI, DMI, ATR, Hurt and REX are between satisfactorily and very good,[15] while CCI and Stochastics are both on a very good level.

Key figures for distinct market cycles

In the section Material and Methods, four different market cycles were introduced. The one computed upfront and two-dimensional key figures are also computed in the cycles. The results are presented in tabular fashion and show whether the respective factor is better compared to the benchmarks (1 = green) or not (0 = red). Additionally, the rightmost column of Table 2 computes how much better the factor is in percent compared to the respective cycle.

Factor vs. S&P 500

Table 2 shows in its the upper part a comparison between the factors and the S&P 500. These outperform annualized returns in a sustained manner, only considering higher volatility, however, particularly during market cycles MC2, MC3 and MC4. Predominantly worse are the maximum drawdowns of all factors, whereby cycles MC3 and MC4 are to be emphasized. With regard to the two-dimensional key figures, it was found that mainly in all market cycles, increased risk was compensated by higher returns.

Table 2. One- and two-dimensional key figures in different market cycles

S&P500 vs.		S&P500	1_RSI	2_DMI	3_MACD	4_RoC	5_Bollinger	6_CCI	7_Stochastics	8_ATR	9_Hurst	10_REX	in Percent better
Annualized Return (%)	MC1	-	1	1	1	0	0	1	1	1	1	1	80
	MC2	-	1	1	1	1	1	1	1	1	1	1	100
	MC3	-	1	1	1	1	1	1	1	1	1	1	100
	MC4	-	1	1	0	0	1	1	1	1	1	1	80
Volatility	MC1	-	0	1	0	0	1	1	1	1	1	0	60
	MC2	-	0	1	0	0	0	1	0	1	1	0	40
	MC3	-	0	1	0	0	0	1	0	1	1	0	40
	MC4	-	0	1	0	0	0	1	0	1	1	0	40
Max Drawdown (%)	MC1	-	0	1	0	0	0	1	1	1	1	0	50
	MC2	-	0	1	0	0	0	1	1	1	1	0	50
	MC3	-	0	0	0	0	0	0	0	0	0	0	0
	MC4	-	0	0	0	0	0	0	0	0	0	0	0
Sharpe Ratio	MC1	-	1	1	1	0	0	1	1	1	1	1	80
	MC2	-	1	1	1	1	1	1	1	1	1	1	100
	MC3	-	1	1	1	1	1	1	1	1	1	1	100
	MC4	-	1	1	0	0	1	1	1	1	1	1	80

SPX500 EQW vs.		S&P500	1_RSI	2_DMI	3_MACD	4_RoC	5_Bollinger	6_CCI	7_Stochastics	8_ATR	9_Hurst	10_REX	
Annualized Return (%)	MC1	1	1	0	1	0	0	1	1	0	1	1	60
	MC2	1	1	0	0	0	1	1	1	1	0	0	50
	MC3	1	1	1	0	0	0	1	1	1	1	1	70
	MC4	1	1	1	0	0	1	1	1	1	0	0	60
Volatility	MC1	1	0	1	0	0	0	0	0	1	0	0	20
	MC2	1	0	1	0	0	0	0	0	0	0	0	10
	MC3	1	0	1	0	0	0	0	0	0	1	0	20
	MC4	1	0	1	0	0	0	0	0	0	1	0	20
Max Drawdown (%)	MC1	1	0	0	0	0	0	1	0	0	1	0	20
	MC2	1	0	0	0	0	0	0	0	0	1	0	10
	MC3	0	0	1	0	0	0	0	0	0	1	0	20
	MC4	0	0	1	0	0	0	0	0	0	1	0	20
Sharpe Ratio	MC1	1	0	0	0	0	0	1	1	1	1	0	40
	MC2	1	0	0	0	0	0	1	0	1	0	0	20
	MC3	1	1	1	0	0	0	1	1	1	1	0	60
	MC4	1	1	1	0	0	0	1	1	1	0	0	50
Information Ratio	MC1	-	1	0	1	1	0	1	1	0	1	1	70
	MC2	-	0	0	0	0	0	0	0	0	0	0	0
	MC3	-	0	1	0	0	0	1	1	1	1	0	50
	MC4	-	0	1	0	0	0	1	1	1	0	0	40

Factor vs. S&P 500 EQW

In the lower part of Table 2, a comparison is made against the S&P 500 EQW. The results are worse throughout. The key figures for the factors MACD, RoC and Bollinger turned out poorly for all market cycles and confirm the negative results throughout the considered time period.

For almost all factors, market cycle MC2 from 2000 to 2007 was the most difficult to perform in. Only 50% of the factors could outperform the benchmark, whereas only one factor shows a lower volatility, specifically maximum drawdown. Also the two-dimensional key figures are smaller than 30%. In fact, the information ratio is 0%.

The results for DMI, CCI, Stochastics and ATR are prdominantily positive. The higher risks were mostly compensated by outperformance. The respective results are stable. This means, for example, that factor stochastics, which accumulated the highest return, was at the same time superior in each market cycle.

Correlation and rolling 12-month correlation

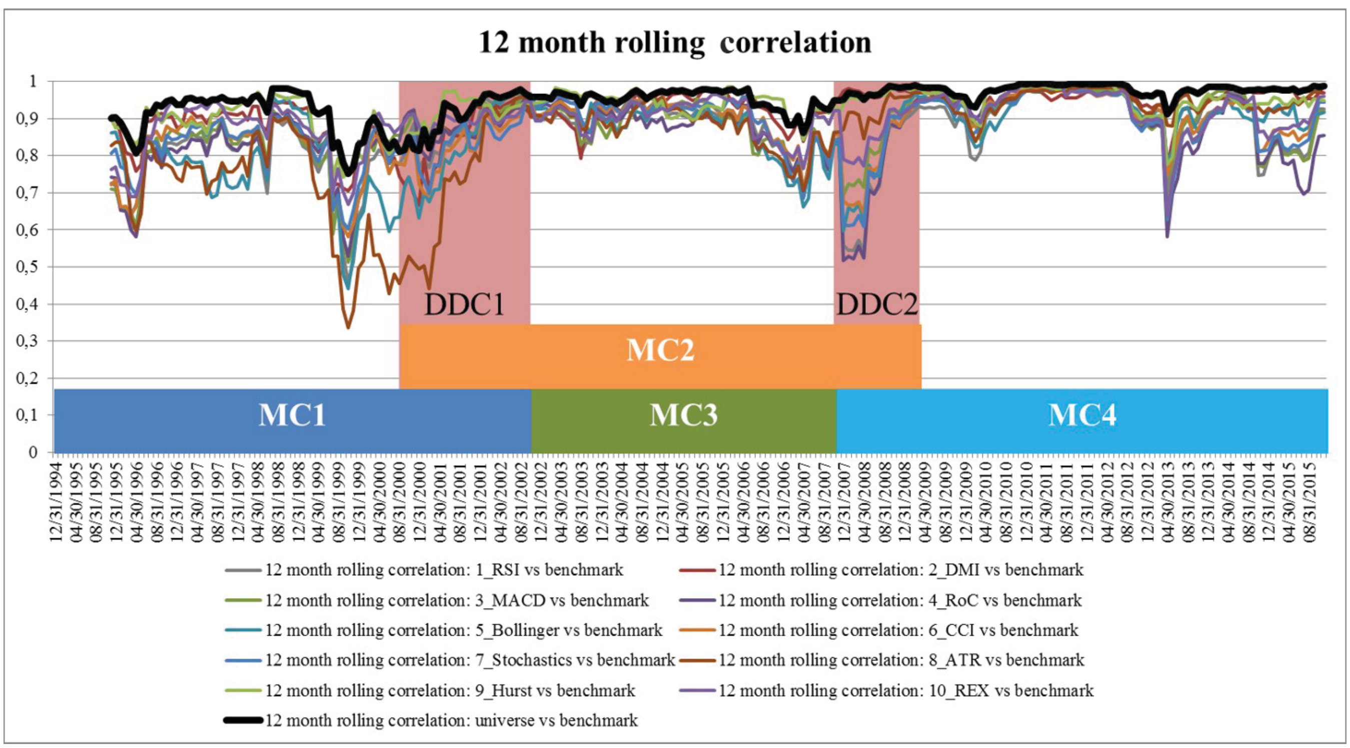
To investigate the interrelation between the factors' returns compared to the S&P 500 benchmark, a monthly correlation is calculated. In case of no co-movements, the correlation is zero. In case of a perfect co-movement between factor and benchmark, the correlation is equal to one.

During the considered time period, the correlations are between 0.81 and 0.93. The average correlation is 0.87. This high correlation is to be interpreted to be indeed normal.

Since correlation is not constant in time and as a sole figure has limited meaningfulness, the rolling correlation over a time window of 12 months is shown in Figure 6. The correlations change with time and vary between highly correlated movements, characterized by values above 0.9, and intermediary correlated movements, indicated by values smaller than 0.5. It is noted that correlation begins to fall several months prior to new highs of a market cycle, specifically prior to the downtrends of 2000/2002 (DDC1) and 2007/2009 (DDC2). It is beyond the scope of this thesis to assess whether the factors indeed predict shifting market cycles.

During the downtrends DDC1 and DDC2, correlations increase again. This is in agreement with the previously computed risk measures, since the factors clearly achieve higher drawdowns. During stable and strong uptrends, correlations take values around 0.9. While distinct differences are observed during market cycle MC1, they tend to narrow during cycle MC3 and MC4.

Figure 6. 12-month rolling correlation of factors and S&P 500 EQW vs. S&P 500



Throughout the higher correlated are the factors Hurst and DMI. Weakly correlated are, however, RoC, Bollinger, CCI, Stochstics and ATR, whereby correlations change over time. Only minor influence on correlation seems to have equally weighted the portfolio. The S&P 500 EQW (black line), by tendency, correlates higher and more stable compared to the factors.

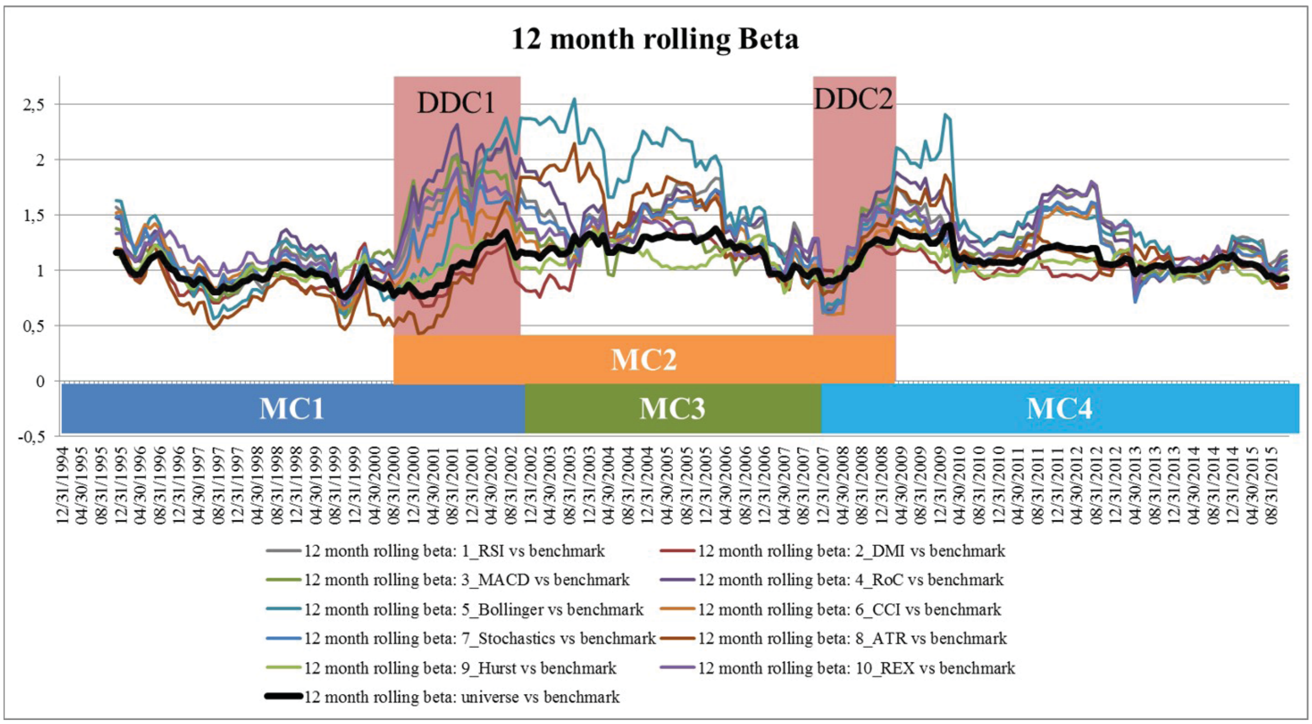
Rolling 12-month beta

Beta displays the systematic market risk. Depending on the market situation, a high or low beta is preferred. Figure 7 displays the rolling beta with a time window of 12 months since beta is not constant in time and has limited meaningfulness as a single measure.

Smart beta/stupid beta of the factors

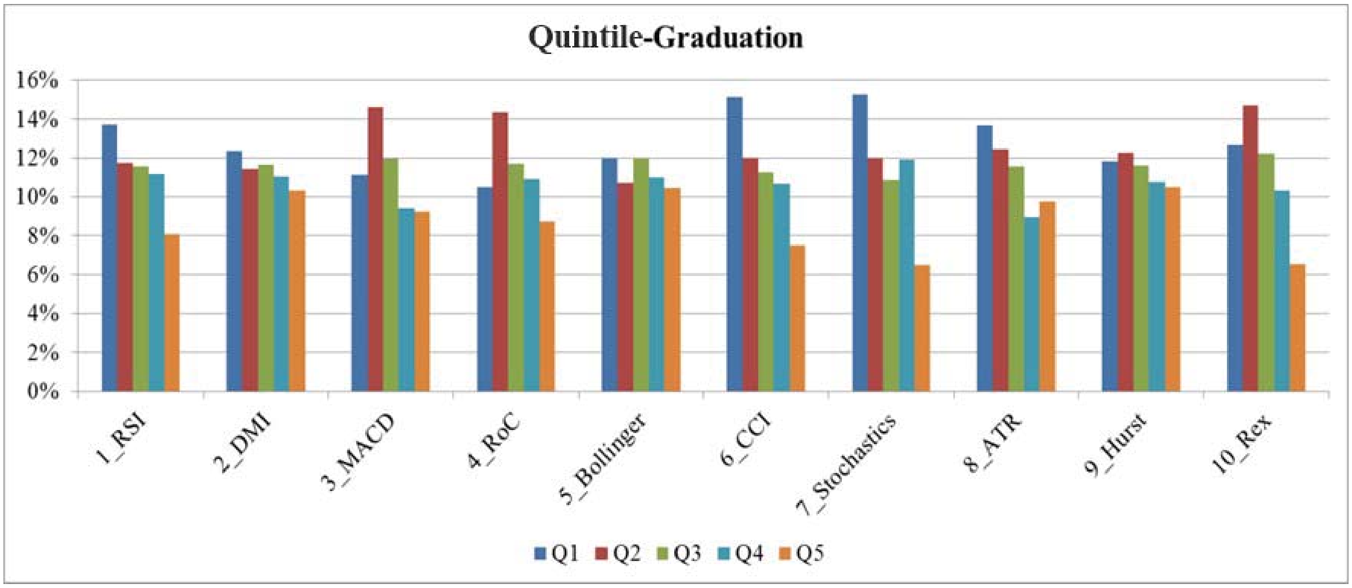
On the foundation of the respective first quantile, the surplus value of the factors have already been outlined. To test the "prediction capability" and whether the results are obtained in a constant or random fashion, the results of the remaining quantiles also are compared in the following. This is due to the fact that the existence of smart beta necessarily implies the existence of a "less smart" or even "stupid beta". To investigate this, for each factor, the annualized returns of the quantiles are compared against the overall cycle. For those factors resulting in a decreased return from first to fifth quantile, a higher predictability is assumed. Factors whose first quantile do not bear their highest return and whose last quantile does not bear their lowest return are assumed to have rather limited predictability.

Figure 7. 12-month rolling beta of factors and S&P 500 EQW vs. S&P 500



Note: The black line shows the beta of the S&P 500 EQW compared to the S&P 500. Clearly, the factors yield higher betas over time. They are positive during stable uptrends like MC1 and MC4. Additionally, the biggest outperformance is generated during these cycles. Hence, the factors during these phases carry good skills of selecting the most attractive stocks. However, they fail just during times in which not high but low beta is demanded. Beta increases significantly during the bad phases DDC1 and DDC2.

Figure 8. Quintile-Graduation of factor portfolio Q1 until Q5



Note: The factors RSI and CCI show a clear decline regarding annualized returns. DMI, Bollinger, Stochastics and ATR achieve at least in quantile 1 their highest and in quantile 5 their lowest returns. For MACD, RoC, Hurst and Rex, quantile 2 partially bears the distinctly higher returns. Regarding the difference in returns between the first quantile (Q1) and the fifth quantile (Q5) (i.e., the quantile spread [QSpread]), RSI, CCI, Stochastics, ATR and Rex appear to have a pronounced positive difference.

Statistics

In a further step, ordinary least squares (OLS) models are built to analyze the returns of the S&P 500 in comparison with the returns achieved by the factors. Regression models are widely used in practice. Although they were used in the past mostly to explain stock prices based on fundamental data (e.g., the book-to-market value of a particular company), in this thesis, it is pioneered to take a similar approach on factors from TA. OLS assumes that the factors serve as independent variables to explain the returns of the S&P 500. Subsequently, the returns of the S&P 500 were regressed on a slope coefficient and a constant using the software Stata 13.[16] This resulted in 10 linear models, one for each factor.

Since the p-value for the F-statistic for each of the factors is smaller than 0.05, in fact even close to zero, we are able to reject their null hypothesis (i.e., that their R2 is zero) at the 5% and even the 1% significance level in favor of the alternative hypothesis (i.e., that all the models have some explanatory power). In fact, we can say that we are more than 99% confident that the obtained models explain some variation of the monthly returns of the S&P 500.

Furthermore, all investigated factors are evaluated to be statistically significant, too, in terms of explaining the variation of the monthly returns of the S&P 500 since we equally reject each of their null hypothesis at the 5% significance level. Taking the coefficient of determination into consideration, the best factors explaining the data were Hurst, DMI and Rex. They have R2 values between 80.79 and 86.64%, while the worst factors in terms of R2 are RSI, Bollinger and ATR, with 72.42 to 66.31%. It is noted that the t and p-values for the regression results are indeed quite high and low, respectively.

The data to be explained were the returns of the S&P 500, while the independent variable was each of the factors, one factor at a time.

Table 3. Statistical details for the linear regression results

		1_RSI	2_DMI	3_MACD	4_RoC	5_Bollinger	6_CCI	7_Stochastics	8_ATR	9_Hurst	10_Rex
	F(1, 250)	656,29	1232,67	847,95	747,81	579,88	731,54	730,76	492,15	1621,62	1051,52
	Prob > F	0	0	0	0	0	0	0	0	0	0
	R-squared	0,7242	0,8314	0,7723	0,7495	0,6988	0,7453	0,7451	0,6631	0,8664	0,8079
	Adj R-squared	0,723	0,8307	0,7714	0,7484	0,6975	0,7443	0,7441	0,6618	0,8659	0,8071
Factor	t	25,62	35,11	29,12	27,35	24,08	27,05	27,03	22,18	40,27	32,43
	P>I t I	0	0	0	0	0	0	0	0	0	0
Constant	t	0,89	-0,52	1,46	1,97	1,64	-0,15	0,06	0,65	-0,33	0,83
	P>I t I	0,376	0,606	0,145	0,05	0,102	0,877	0,953	0,513	0,742	0,407

Discussion

Indicators in Technical Analysis — Sustainable and systematic return

Indicators in TA fulfill the assumed features for smart beta strategies. Yet, the economic fundament needs to be replaced by the philosophy of TA, which is probably challenged by parts of the finance industry mostly relying on fundamental analysis. By doing so, however, critics have to challenge the widely accepted and applied factor "momentum" as well.

The monthly selection of 100 stocks for the factor portfolio was based on each stock's factor score. For each stock, a lower factor score is regarded to be better than a higher one. The factors DMI, MACD, ROC and CCI are indicators measuring trend and/or momentum. Judging solely for TA literature, a lower factor score should be assumed. By doing so, however, the results would be significantly worse.

All factors based on TA achieve higher overall and annualized returns compared to the market capitalization weighted S&P 500. In contrast, however, the risk measures are predominantly worse. The two-dimensional risk-adjusted key figures show that the higher risks for the factors RSI, DMI, CCI, Stochastics, ATR, Hurst and REX are, however, overcompensated. The results for market cycles MC1 to MC4 are similarly constant, excluding RSI and REX, which are constantly worse regarding risk.

The monthly computed S&P 500 EQW should be considered to be the fair, thus harder benchmark. Although the performance is better for eight of 10 considered factors, their risks are predominantly higher as well. Hence, their two-dimensional key figures are worse. Notable are the results for the Information Ratio over the whole market cycle, which are interpreted that the largest fraction of the systematic and consistent outperformance is due to the equally weighted portfolio and not the actual selection of 100 stocks. Accordingly, only the factors CCI and Stochastic are better. The factors MACD, RoC and Bollinger even skimm off the systematic and consistent base of equally weighted. Nonetheless, the results in the different market cycles are better.

The results of the one- and two-dimensional key figures are that the factors are capable of generating risk-adjusted returns which are, according to the Information Ratio, only systematic and consistent for CCI and Stochastic.

The rolling correlations and betas further characterize the factors. In uptrends lasting several months, correlations decrease to middle levels; betas generally to around one. In these instances many factors demonstrate their surplus value. Their bad characteristics appear in bear markets or shortly after. Their correlations are close to one and the betas way above the market beta. Equally weighted then has limited effects. Further analysis gives some indication in terms of the results' sustainability. The smart and stupid beta tests show the factor-generated quantiles mostly show a clear graduation.

Regarding the ordinary least squares regression, all factors were found to be statistically significant at the 5% level (i.e., all of them do explain parts of the returns obtained by the S&P 500 reasonably well). Out of the 10 factors, the best in terms of coefficient of determination (R2) were Hurst, DMI and Rex. They showed an R2 between 80.79 and 86.64%, while the worst factors were RSI, Bollinger and ATR, whose R2 decreased from 72.42 to 66.31%.

The t and p-values for all the factors were extraordinarily high and low, respectively. It is noted that linear regression results in basic models that cannot explain extreme market events, particularly their behaviourism, or events exceeding the ones inherit by the data. More complicated models taking, for example, possible multicollinearity or non-linearity into account could be closer to reality.

Implementation and relevance for practitioners

The factor portfolios are assembled on a monthly basis, and input parameters for the factors were selected discretionary. As a matter of fact, varying input parameters will affect the results.

Maintanance and transaction costs are not taken into account, though, they negatively affect outperformance. Monthly turnovers are generally between 60 and 70%, which is very high. However, transaction costs have decreased substantially in recent years, allowing implementation of the strategy in practice. ETFs being allocated monthly already exist.

In practice, several weighting methods, specifically alternative weighted methods, exist, such as book value, dividend, turnover and low volatility. This could also be realized for the analyzed factors. The factor portfolios do not consider risk concentration and liquidity risk, which indeed needed to be hedged or accounted for in practice.

Besides direct implementation in strategies and systematic equity research, the combination of factors based on FA and TA can have surplus value as well. For example, in a first step, a selection of fundamentally cheap stocks could be done, while in a second step, factors from TA select those showing a positive price trend.

This thesis covered 10 indicators, which is only a fraction of the quantitative methods (classical) indicators available in TA. Technological progress and ever-growing possibilities to quantitatively register, for instance, price patterns or Elliot Waves, allow for considerably enlargement of the search space for factors in systematic equity research.

In the author's opinion, this could result in two important proceedings for TA. On one hand, a direct comparison between TA and FA would be possible on a broad empiric foundation; on the other hand, evidence underlining the relevance of methods from TA would be provided.

Conclusion

This thesis demonstrates that by using indicators from technical analysis in the context of systematic stock selection, smart beta is obtained. The indicators are simple, transparent and obtained, respectively implemented, using a rule-based process. Over two decades and considering different market cycles, it was shown that almost every considered indicator achieved higher systematic, risk-adjusted returns than the benchmarks S&P 500 and monthly equally weighted S&P 500. Using a variety of tests and key figures, the strengths of the factors in uptrends and weaknesses in downtrends were demonstrated. The obtained results are sustainable and significant. It is recognized that neither of the factors are the single cause of price movements in the markets and thus to some extend symptoms not having a distinct economic reason. Yet, they are undoubtedly present, not casued by randomness and tested on a broad empirical framework.

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Notes

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Time Cycle Oscillators

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Abstract

In the field of technical analysis, time cycles are used to identify price turning points. The lows are normally used to define the cycle periods—which are uniform—to anticipate the lows for future time intervals. Therefore, some discrepancies such as inversions and phase shift occur due to the non-uniform price movement. In this article, new time cycle oscillators are introduced to technical analysis. The role of the oscillators is to measure the irregular cycle periods. Besides, mathematical steps are taken to prove that cycle periods precede volumes. Several systems in nature exhibit periodic motion with different types of oscillations. In this article, a scientific approach is introduced to measure the periods of cycles. Time cycle oscillators pave the way to analyze the market weaknesses and strengths from a time perspective.

Introduction

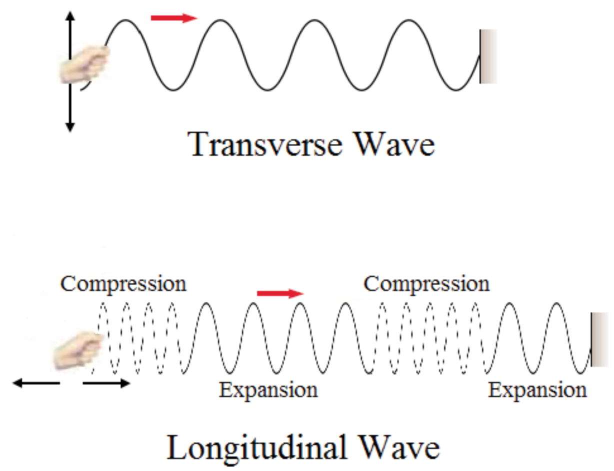
Cycle Discrepancy

We find oscillatory motions in several systems in nature. For example, "the molecules in a solid oscillate about their equilibrium positions; electromagnetic waves, such as light waves, radar, and radio waves, are characterized by oscillating electric and magnetic field vectors" (Serway and Jewett, p. 453). Since the cyclic movement of price is non-uniform, a discrepancy in uniform measurements appears like cycle inversions, which are very difficult to be observed. An inversion is when a cycle low is expected to occur but a peak is formed instead. Another aspect is the phase shift when cycles frequently change their periods. The aim of this article is to approach an alternative method and to measure the irregular period of cycles through new leading oscillators: wave period oscillator, simple harmonic index, and simple harmonic oscillator. In addition to time cycle oscillators, a new method is proposed to lead prices and oscillators by phase.

Properties of Waves

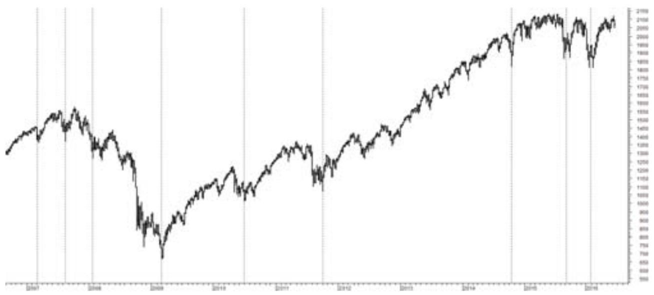
There are two types of waves in nature: transverse and longitudinal. A transverse wave is a traveling wave that causes the elements of the disturbed medium to move perpendicular to the direction of propagation. A longitudinal wave is a traveling wave that causes the elements of the medium to move parallel to the direction of propagation.

Figure 1. Transverse and Longitudinal Waves



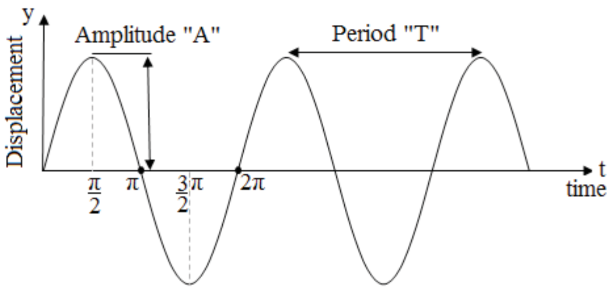
In Figure 1, the wave runs in series of compressions and rarefactions (expansions). A compression is a region in a longitudinal wave where the particles forming the wave are closest together. A rarefaction is a region in a longitudinal wave where the particles are furthest apart.

Figure 2. S&P 500—Weekly Values



In Figure 2, during the periods of 2007–2008 and Q4 2014–2016, the S&P 500 cycles are compressed as the index moves sideways. The distance between the lows decreases. During the period of 2008–Q4 2014, the cycles are expanded as the index moves in trend. The distance between the lows increases, while the trend is running with more power.

Figure 3. Displacement versus time for simple harmonic motion



A simple harmonic wave or ideal wave of price has a relation between price displacement from equilibrium and time. This relation is expressed by:

$$y = A \sin(\omega t + \varphi)$$

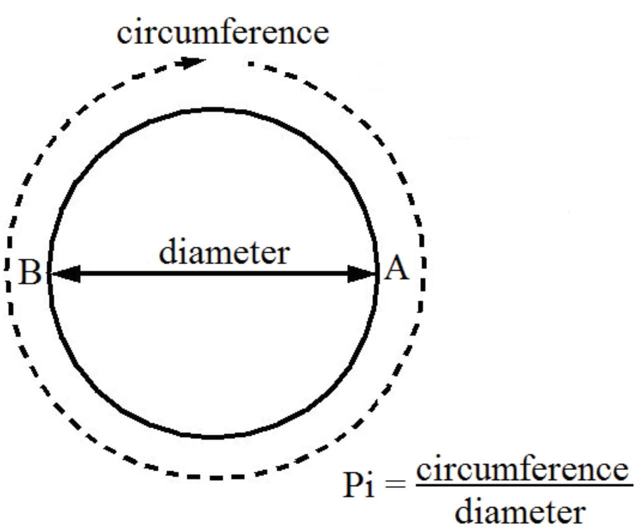
Where the amplitude *A* is the maximum displacement of the price from its equilibrium. The angular frequency ω is the number of cycles per unit time. The quantity $(\omega t + \varphi)$ is called the phase of the motion while the phase constant φ, is the difference between two successive waves. In this article, φ is equal to zero, assuming that any cycle starts from its reference point with no phase shift. So, $(\omega t + \varphi)$ will be expressed by θ. Hence,

$$y = A \sin(\omega t) \quad \text{Or} \quad y = A \sin \theta$$

$$\omega = 2\pi f$$

Where the frequency *f* is the number of cycles per unit time. Pi π is a mathematical constant approximated to 3.14 and is defined by the ratio of a circle's circumference to its diameter. A body in motion completes half cycle when it moves on the circumference from point A to B. π is equivalent to a half cycle while 2π or 6.28 is equivalent to one complete cycle (360 degree).

Figure 4. Definition of the mathematical constant (Pi)



The period *T* of a wave is the time interval required to form two identical points such as the peaks of adjacent waves. The period is the inverse frequency of a wave, hence,

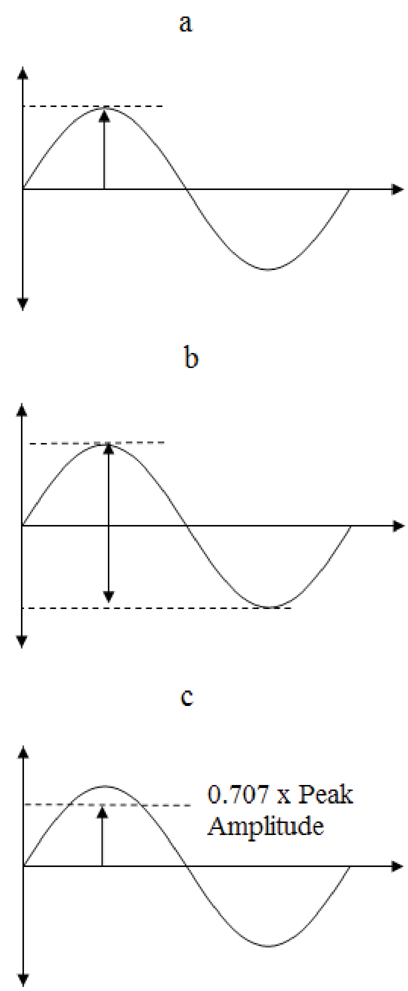
$$T = \frac{1}{f}$$

Where its unit is time (number of price bars) per one cycle. Eventually, we can rewrite the first equation as the following,

$$y = A \sin\left(\frac{2\pi}{T} t + \varphi\right)$$

Although the previous equation yields one result for the wave amplitude, we may represent the amplitude by three different means as shown in Figure 5. The most widely used is the peak amplitude representation especially in astronomical measurements of nearby stars, audio system measurements, and telecommunications. The peak-to-peak amplitude of electric oscillations is a direct measurement of oscilloscope devices. This representation was previously proposed by James Hurst. The root mean square amplitude is used in electrical engineering. In this article, we will use the peak amplitude representation.

Figure 5. (a) Peak amplitude (b) Peak-to-peak amplitude (c) Root mean square amplitude



The Phase Lead

Measuring the change in price *(Today's close – Yesterday's close)* is one way to construct a leading oscillator to price. Another method is to calculate the inverse price *(1/Close)* or divide the price by another variable *(Close/High)*. As shown in Figures 6 and 7, the oscillator is leading the price by phase.

Table 1. Price versus inverse price

Day	Price	Inverse Price
1	2.00	0.50
2	2.50	0.40
3	3.00	0.33
4	2.50	0.40
5	2.00	0.50
6	1.50	0.67
7	1.00	1.00
8	1.50	0.67
9	2.00	0.50
10	2.50	0.40
11	3.00	0.33

Figure 6. Price versus inverse price

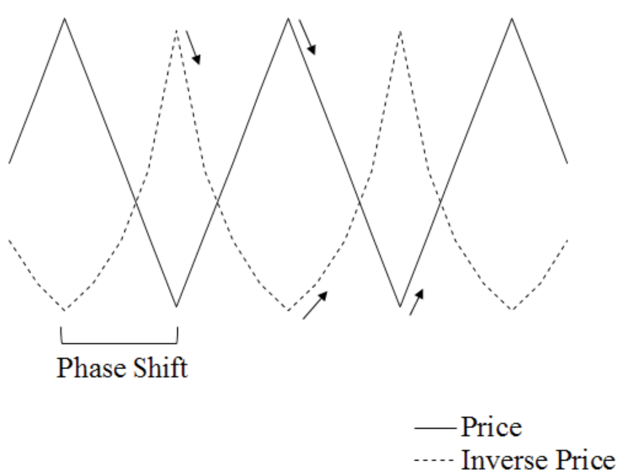
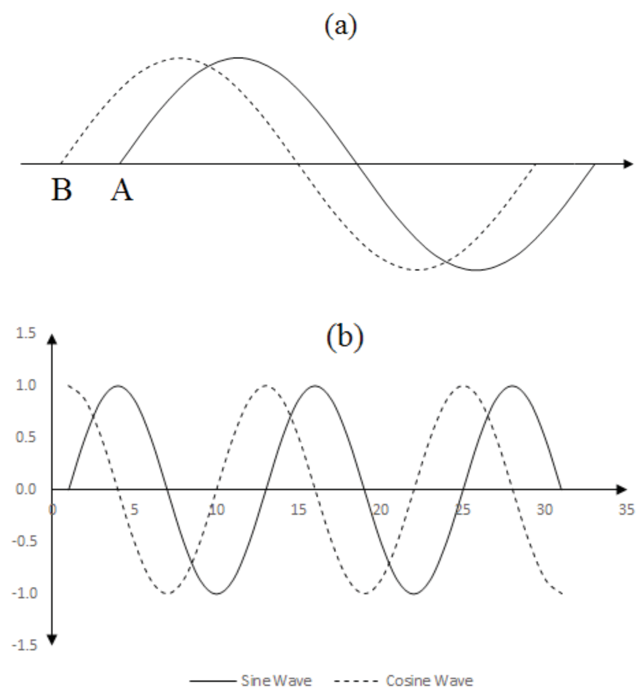


Figure 7. (a) Phase shift between two cycles (b) Sine versus cosine waves



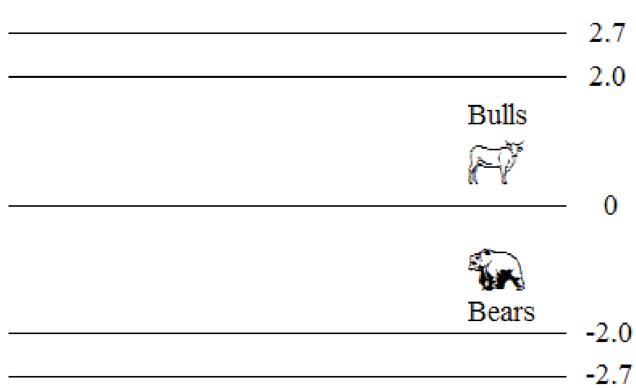
In Figure 6, the inverse prices lead prices by phase. In Figure 7, wave B is ahead of A. In other terms, B leads A. Another method of "phase lead" is by using the sine and cosine functions. For example, if the closing price is x, then cos(x) is leading to sin(x). The phase lead concept allows researchers to create leading oscillators without increasing the number of whipsaws occurring on the equilibrium lines.

Wave Period Oscillator (WPO)

Description

The WPO is a short-term oscillator that measures the buying and selling period of price cycles over a certain time interval. The leading oscillator indicates a rise in buying period when it moves above the zero line and a rise in selling period when it moves below the zero line.

Figure 8. The main boundaries of the WPO



Calculation

$$y = A \sin\left(\frac{2\pi}{T} t\right)$$

The value of time t is the number of days on the chart. For example, t is equal to 1 for the first day and 2 for the second day, etc. In this article, the value of t will be equal to 1 since the aim is to calculate T for each day separately. Therefore,

$$y = A \sin\left(\frac{2\pi}{T}\right) \text{ Or } \; y = A \sin\theta$$

Below is an explanation to the above formula in depth:

- The displacement y is the closing price of today.
- The amplitude can be represented by the high of today or the maximum price within n days ago. A = H or A = Max (C, 3).
- The inverse of the sine function *arcsin* is used to calculate the angle θ in degree.

$$\theta = \arcsin\left(\frac{y}{A}\right)$$

- The aim is to find the wave period which is expressed in decimals. Therefore, θ is converted from degree to radian θ^{rad}.

$$\theta^{rad} = \theta \cdot \frac{\pi}{180^{\circ}}$$

- One-day period T is equal to $2\pi/\theta^{rad}$ or $6.28/\theta^{rad}$.
- When today's price is greater than yesterday's price, the value of T is given a positive sign. If the price is less than yesterday's price, then the value of T is given a negative sign.
- WPO = EMA (T, 14). An exponential moving average is for ±T smoothing while the default parameter of the WPO is 14. However, it can be adjusted for sensitivity or for different timeframes.

Table 2. Data sample for the calculation of one-day period

Day	Closing Price	Amplitude	Sin Angle Sin θr	Angle in Radians θr	Period ±T
t	C	A = High	C/A	arcsin . (sin θr)	6.28t/ θr
1	43.07	43.83	0.983	1.38	4.54
2	43.44	43.9	0.990	1.43	4.40
3	43.54	44.05	0.988	1.42	4.43
4	41.97	43.54	0.964	1.30	-4.83
5	41.99	43.11	0.974	1.34	4.68
6	41.81	42.43	0.985	1.40	-4.49
7	41.22	42.31	0.974	1.34	-4.67
8	41.55	42.01	0.989	1.42	4.41
9	40.98	42.09	0.974	1.34	-4.68
10	41.59	41.75	0.996	1.48	4.23

Longitudinal Waves Setup

The longitudinal price waves, as mentioned before, have successive areas of compressions and expansions during sideways and rallies, respectively. To identify the irregular cycle lines, we shall use the WPO crossovers. First, we add an oversold and overbought levels at periods -2 and +2. The WPO line completes half cycle when it moves from equilibrium to overbought level as the one-day period T is equal to $2\pi/\theta^{rad}$, where θ^{rad} is equal to (180° or π). Therefore, the overbought level has a value of 2 and the oversold level has a value of -2. To trace an extreme overbought level,

- We calculate the difference between the period of half cycle and three-quarters cycle.
- At half cycle T = 2; and at three-quarters cycle T = 1.33.
- Therefore, the difference in periods is equal to 0.66 (2-1.33), which is approximated to 0.7.
- By adding the difference to the half cycle period (+2/-2), the extreme (overbought/oversold) levels will be at (+2.7/-2.7).

When the WPO crosses its extreme levels, this indicates extreme optimism and pessimism. Reaching the extreme levels after price rally shows that prices have attained their maximum momentum and the trend is most likely to be changed.

In Figure 9, the extreme level -2.7 crossover refers to the cycle lows. From mid-June to November 10, the distance between extreme periods of WPO is being contracted. Hence, prices move sideways after November 10. The following cycle lines expand January 17. Afterward, prices move in trend. When the oversold level -2 is used instead of the extreme level, more crossovers and cycle lines are generated. Multiple and near cycle lines like the circled ones in Figure 10 can be considered as a single line. The longitudinal waves setup helps in determining how prices act in the following phase. In case of trending moves, a buy and hold strategy might be favorable. On the other hand, trading a range is used during sideways where cycle lines are compressed.

Figure 9. Egyptian Stock Exchange—Daily Values of Global Telecom (GTHE.CA)

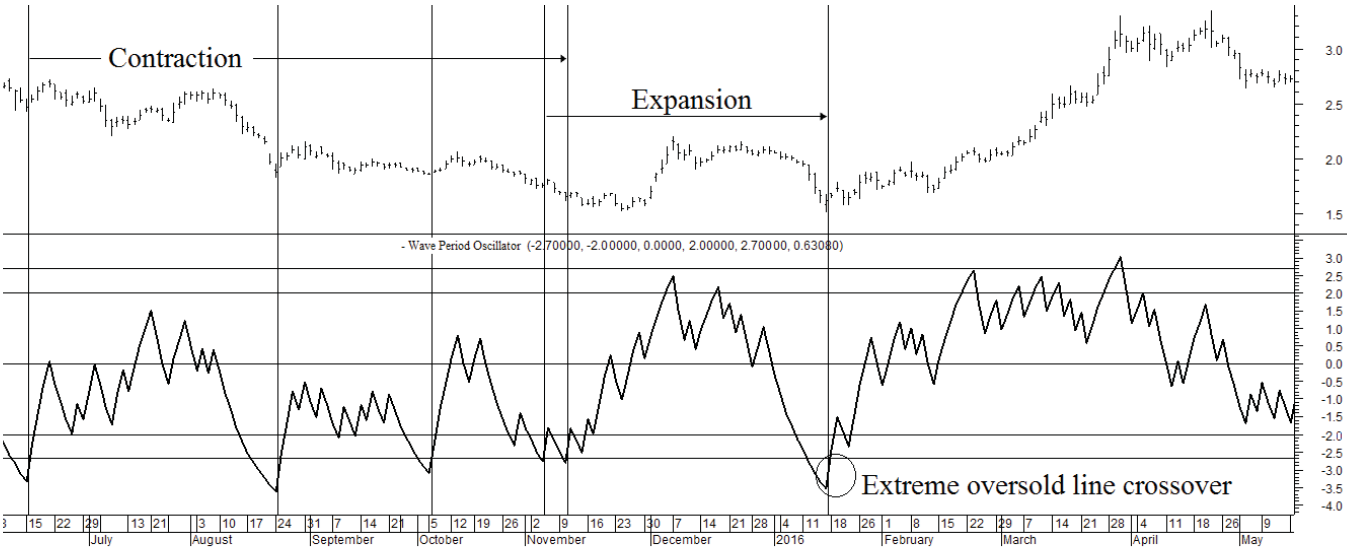
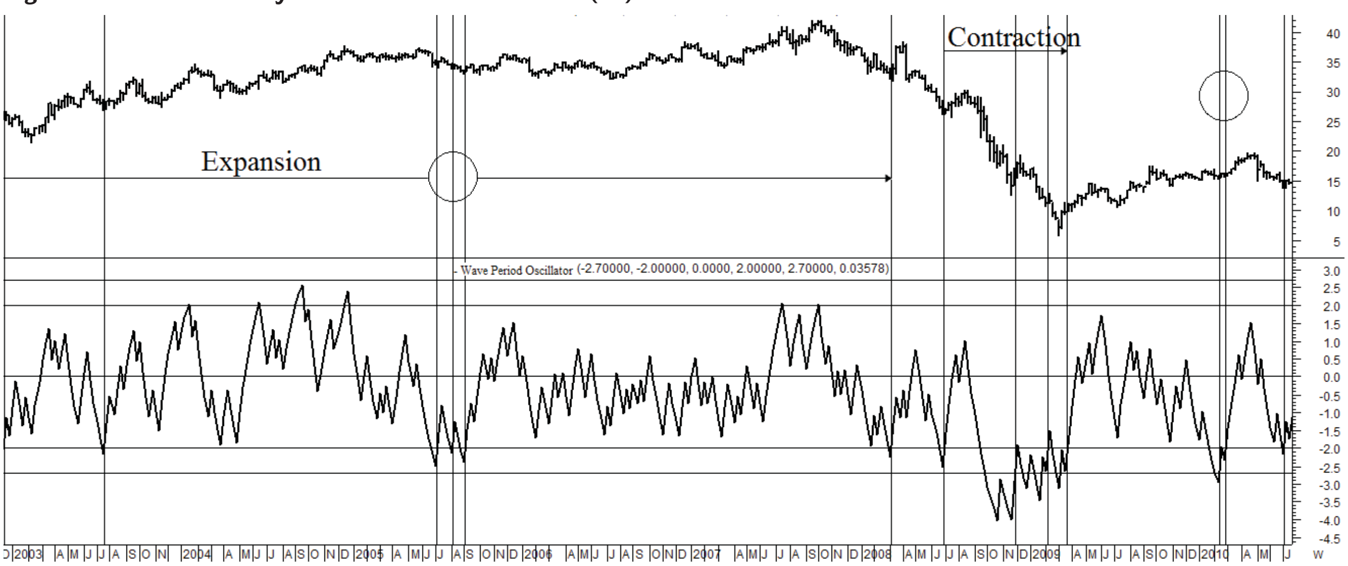


Figure 10. NYSE—Weekly Values of General Electric (GE)



Trading Tactics

Centerline Crossover: As shown in Figure 11, a bullish centerline crossover occurs when the WPO line moves above the zero level to turn positive. A bearish centerline crossover occurs when the WPO line moves below the zero level to turn negative. When bulls are in control, the price rally begins and the average of the bull's period T increases to drive the WPO line above the centerline. A buy signal is subsequently triggered. When the bulls start to loose power, prices move sideway and the average period decreases. In this case, the WPO line may flutter near the centerline and cause false signals, whipsaws. To avoid the whipsaws occuring on the centerline, the following trading tactics are proposed.

Figure 11. Signals of the WPO line

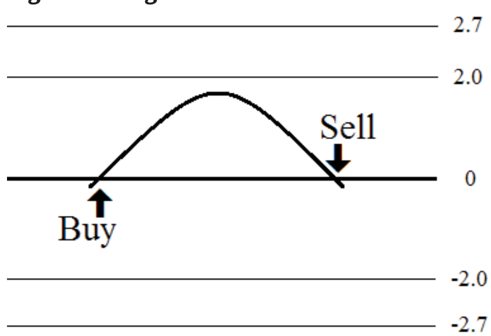
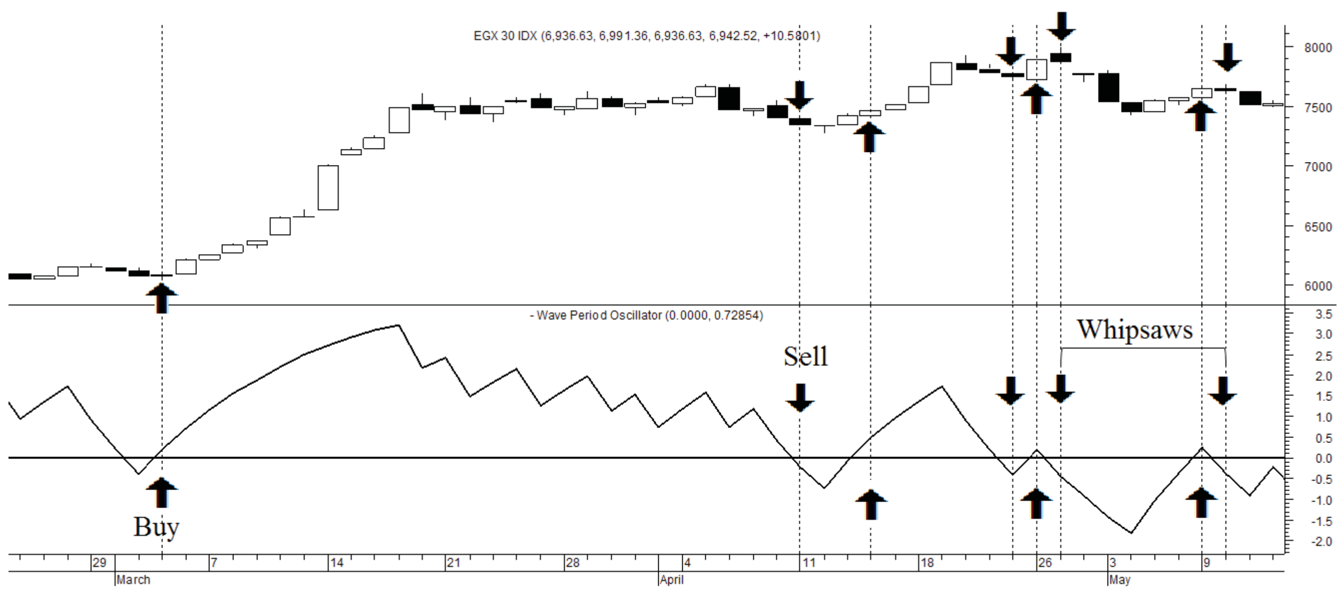


Figure 12. Egyptian Stock Exchange—Daily Values of EGX30 index (.EGX30)



Uptrend Tactic: During an ideal uptrend, the WPO does not reach the lower boundary -2 and usually rebounds from a higher level than -2. This means that the bulls have taken control earlier. Hence, a zero line crossover generates a buy signal. The WPO crosses the upper boundary at +2 then pulls back again below +2 to generate a sell signal, as shown in Figure 13.

Figure 13. Buy and sell signals during uptrend

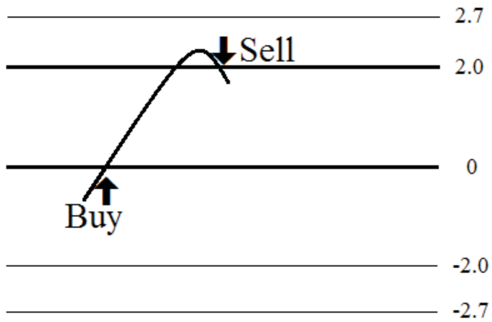
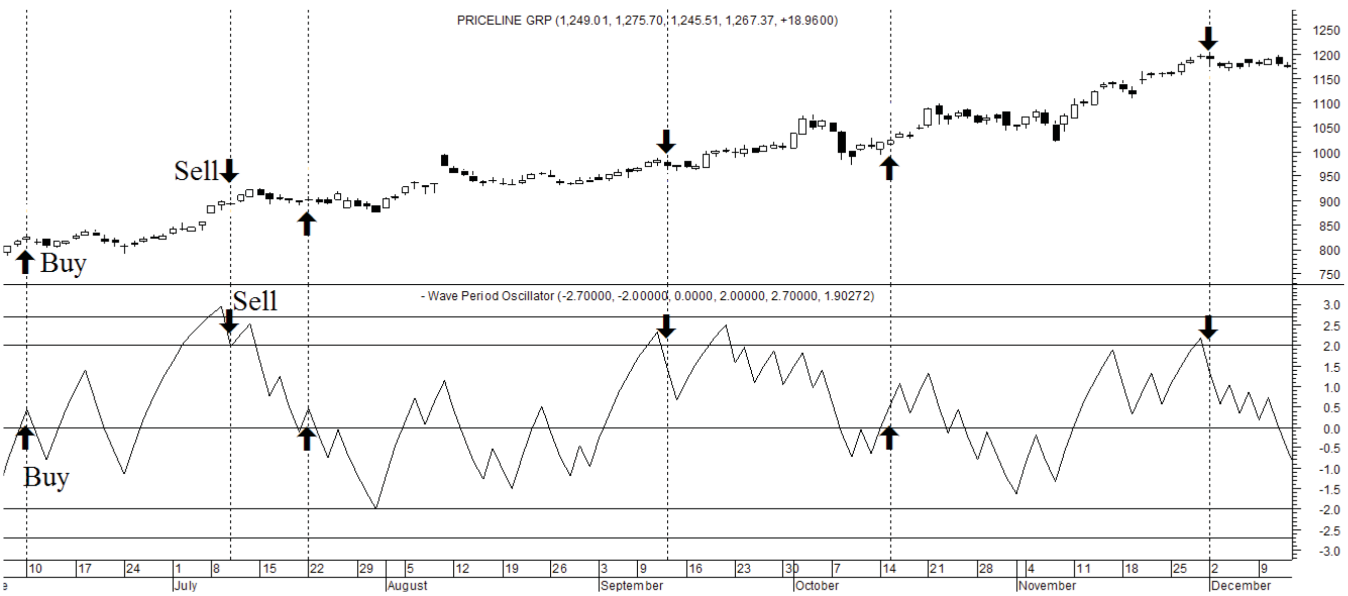


Figure 14. NYSE—Daily Values of Priceline Group (PCLN.O)



Sideways Tactic: During sideways, the WPO fluctuates between the lower and upper boundaries -2 and 2. This tactic is also used in an uptrend where corrections are strong enough to drive the WPO line below the lower boundary.

Figure 15. WPO signals during sideways

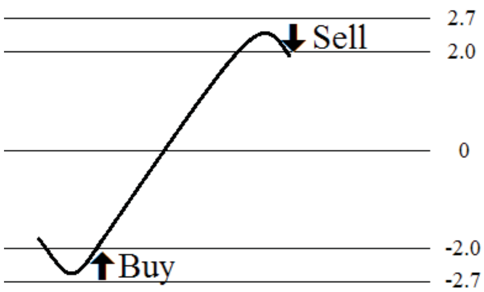
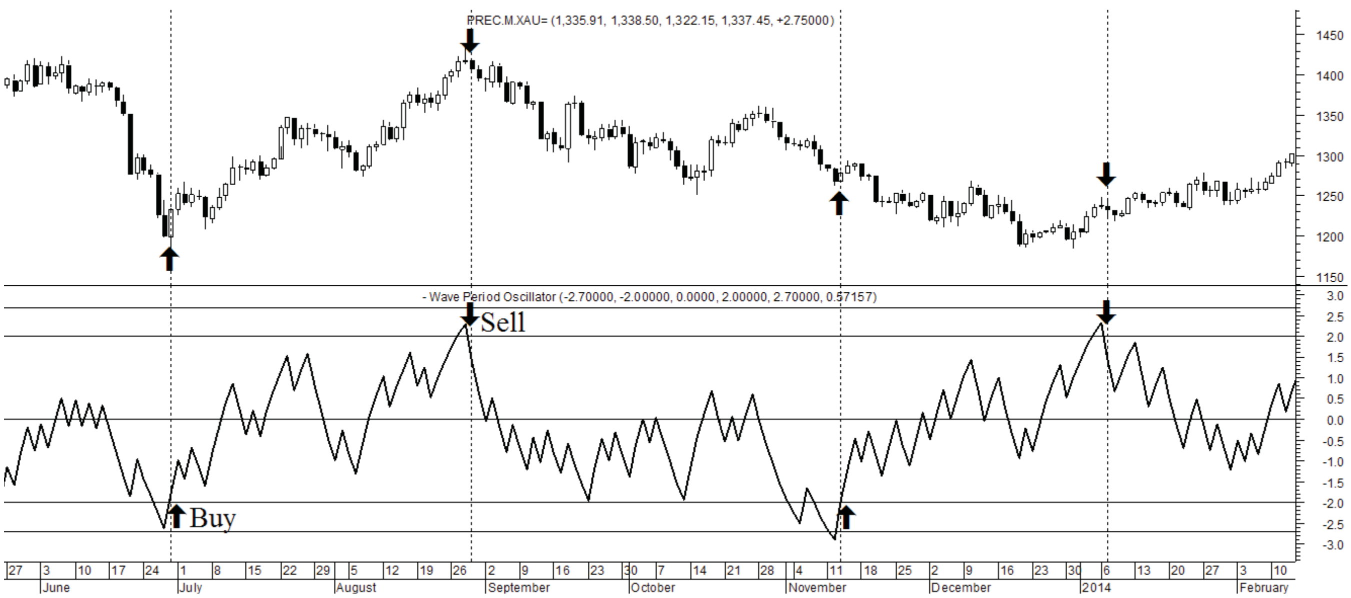


Figure 16. Daily values of Gold (XAU=)



Downtrend Tactic: During downtrends, the WPO fails to reach the upper boundary and oscillates between the 0 and -2 levels. The bears enter early indicating an obvious weakness in the market. Therefore, crossing the zero level generates a sell signal. Figures 17 and 18 demonstrate the WPO behavior during downtrends.

Figure 17. WPO signals during downtrends

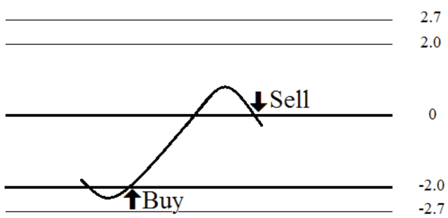
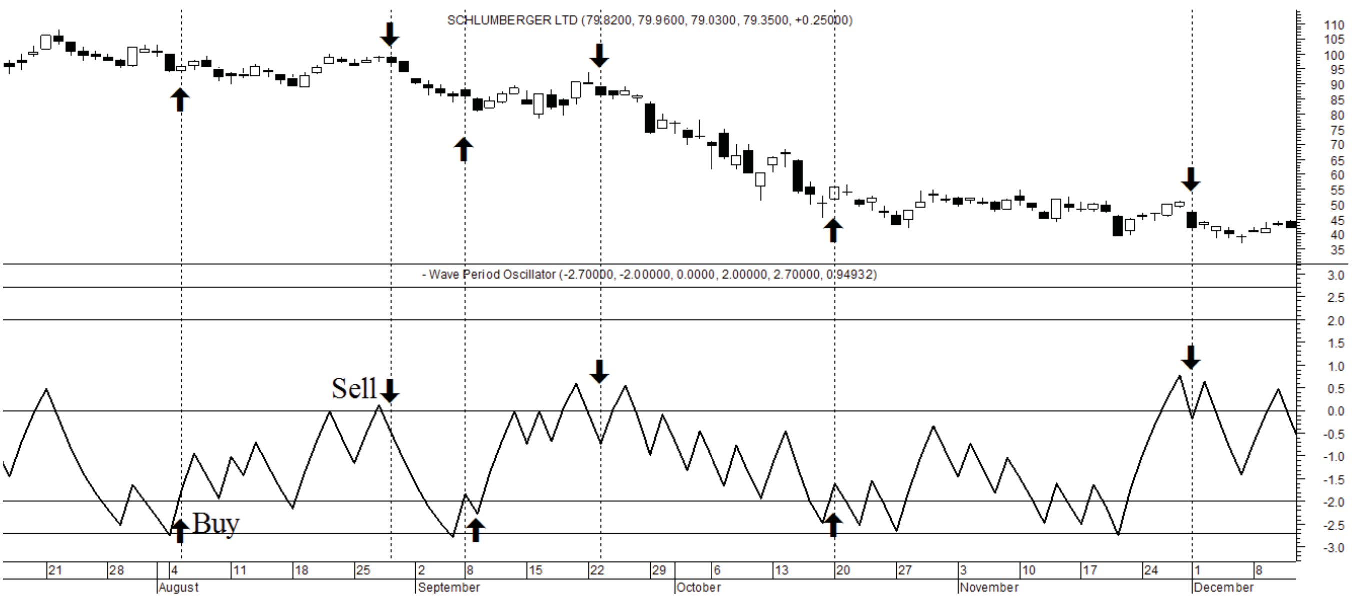


Figure 18. NYSE—Daily Values of Schlumberger Ltd (SLB)



Exit at Weakness: During uptrend reversals and downtrends, the WPO oscillates between the centerline and the lower boundary -2. The bears are controlling the market and move in wide cycle periods while the bull's strength is almost absent. An exit signal is triggered once the WPO crosses -2. When prices decline, the WPO may cross its extreme lower boundary at -2.7, as demonstrated in Figure 19. Therefore, a swift exit signal is triggered once the WPO crosses -2.

Figure 19. Buy and sell signals during uptrend reversal and downtrend

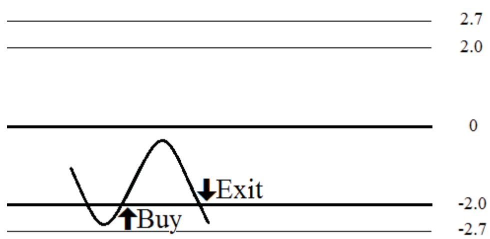
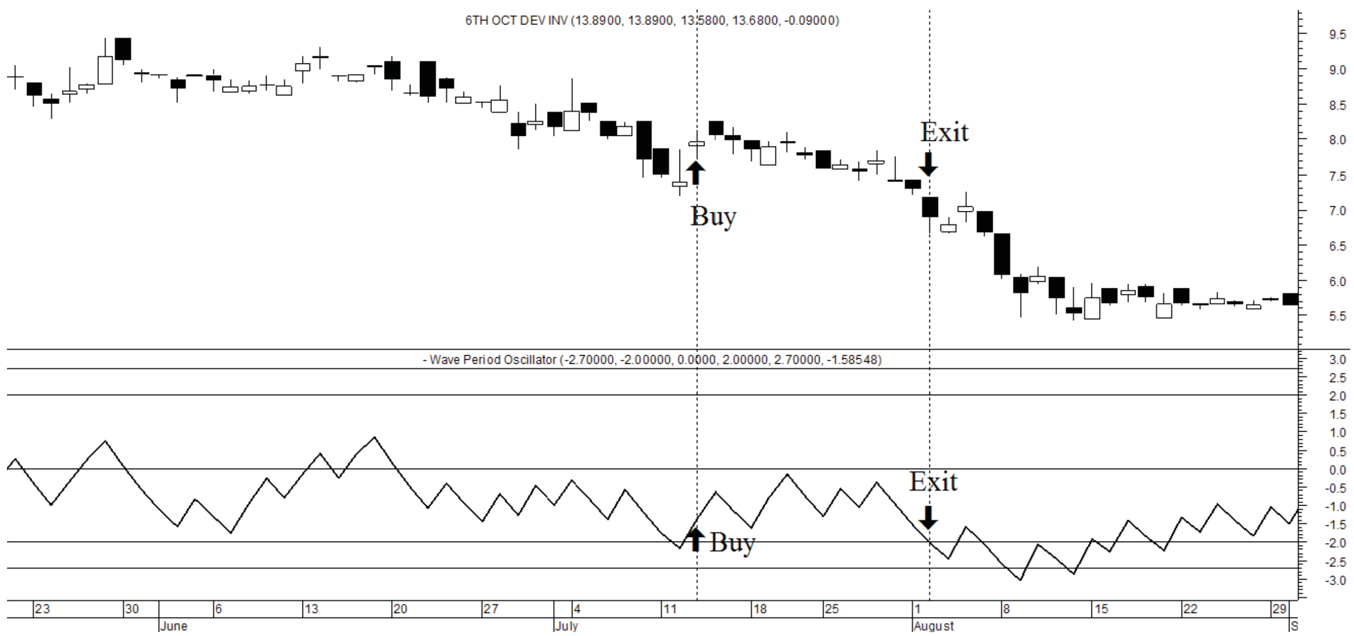


Figure 20. Egyptian Stock Exchange—Daily Values of Six October Development (OCDI.CA)



Re-Entry: During uptrend, the WPO crosses down the upper boundary level at +2 to generate a sell signal. Yet, it does not reach the zero line and the oscillator moves back toward the upper boundary. This case is considered as strength while a re-entry signal occurs at the +2 level crossover. In Figure 21, the WPO is pulled back to the upper boundary +2 referring to high strength in the market. The sell signal is generated when the WPO line crosses down the upper boundary. Figure 22 demonstrates an example for re-entry signals.

Figure 21. Re-entry signals

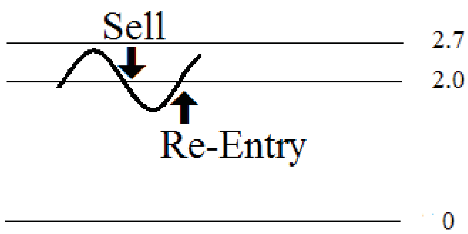
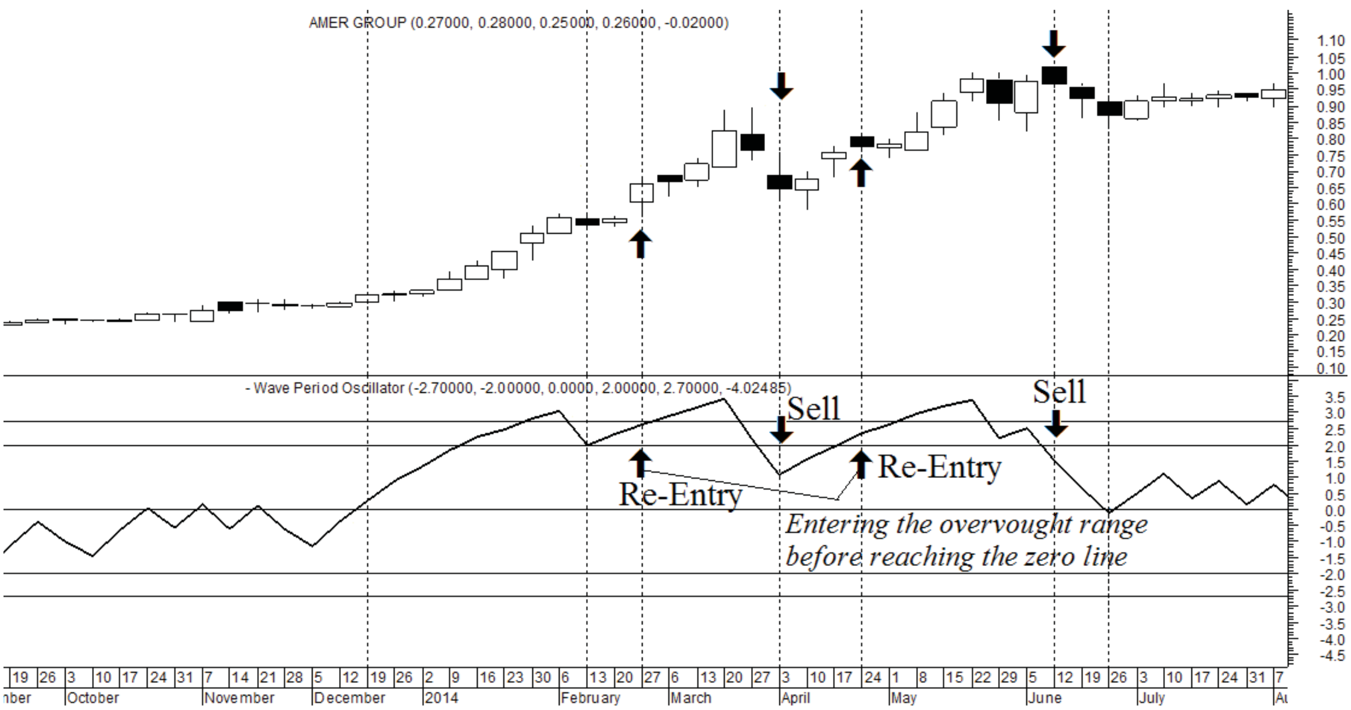


Figure 22. Egyptian Stock Exchange—Weekly Values of Amer Group (AMER.CA)



Divergences

Divergence refers to a situation where technical indicators fail to confirm the price movement. A negative divergence occurs when prices rise and the WPO declines. Conversely, a positive divergence occurs when prices decline and the WPO rises. The high sensitivity of the oscillator increases the odds to have several divergences. Figures 23 and 24 demonstrate examples of divergences.

Figure 23. NYSE—Weekly Values of Dow Jones Industrial Average (.DJI)

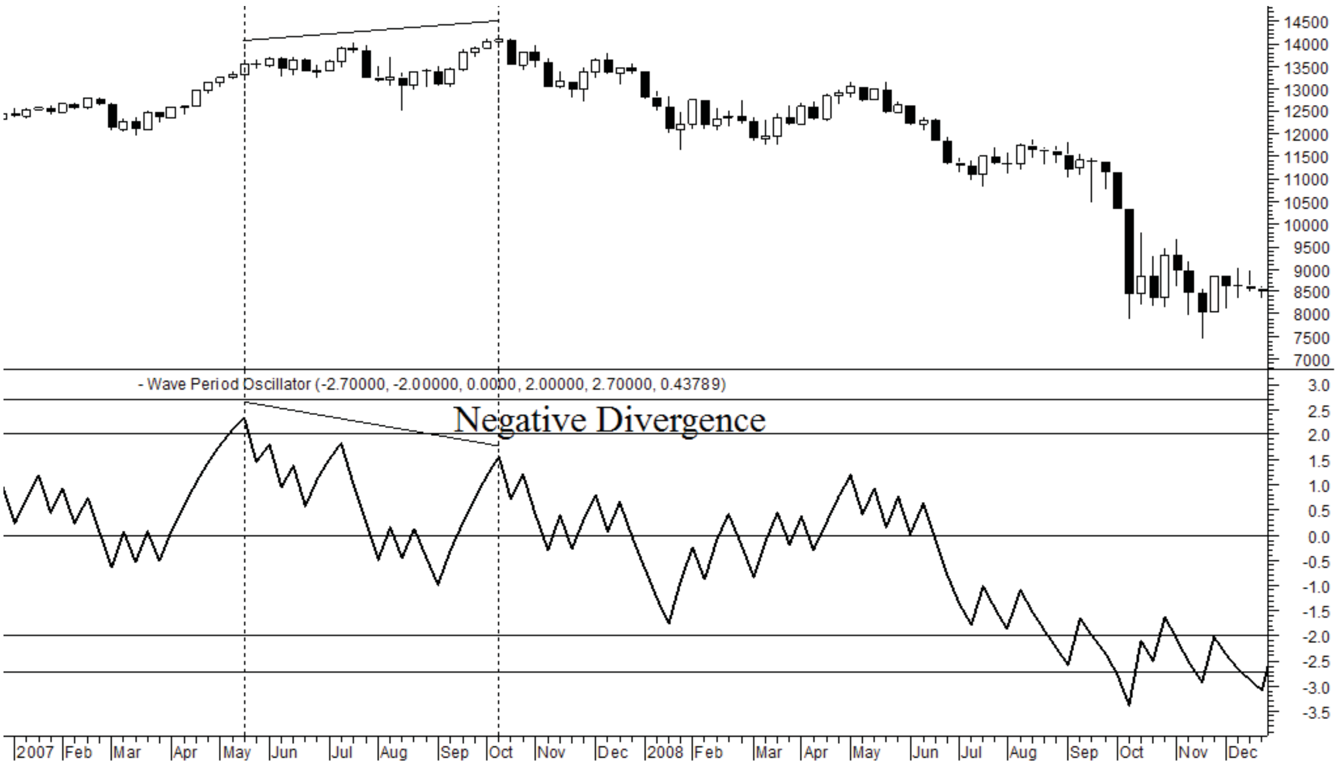
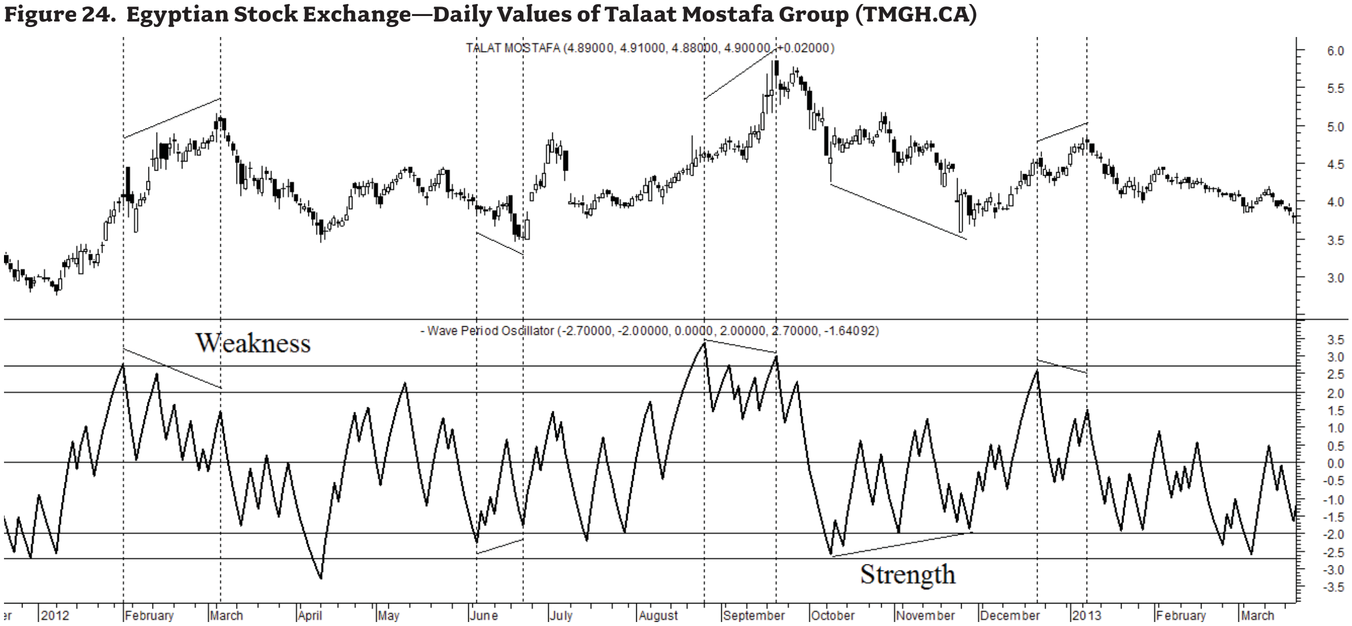


Figure 24. Egyptian Stock Exchange—Daily Values of Talaat Mostafa Group (TMGH.CA)



Simple Harmonic Index (SHI)

Concept

The simple harmonic index (SHI) is based on the derivations of the simple harmonic equation,

$$y = A \sin(\omega t + \varphi)$$

As y is the position of the oscillating wave at a certain time t, the change in positions with respect time expresses the velocity of the wave. Therefore, the velocity is v

$$v = \omega A \cos(\omega t + \varphi)$$

The acceleration α is the change in velocity with respect to time. Therefore,

$$a = -\omega^2 A \sin(\omega t + \varphi)$$

By substituting y in the previous equation,

$$a = -\omega^2 y$$

$$\omega^2 = -\frac{a}{y}$$

By taking the absolute value for both sides of the equation,

$$\omega^2 = \frac{a}{y} \quad \text{and} \quad \omega = \sqrt{\frac{a}{y}}$$

Since "ω is equal to 2πf" and the period T is equal to 1/f then,

$$T = 2\pi\sqrt{\frac{y}{a}}$$

From the last equation, we find that the period of the oscillating price is related to the price displacement and the acceleration by which the price is moving. Unlike the WPO, the period of the SHI is independent of amplitude and phase shift. The simple harmonic index is a leading oscillator which revolves around its centerline. The bulls period increases when the SHI line crosses the centerline to the upside. On the other hand, the bears period increases when the SHI line crosses down the centerline as shown in Figure 25.

Figure 25. SHI Interface

Calculation

Again, the acceleration α is the change in the price velocity with respect to time. If C is the closing price of today, C_y is the closing price of yesterday and C_{by} is the closing price of before yesterday; then, the price velocity of today is expressed by

$$v_t = C - C_y$$

While the price velocity of yesterday is

$$v_y = C_y - C_{by}$$

Hence, the price acceleration of today is expressed by

$$a_t = (C - C_y) - (C_y - C_{by})$$

To reduce the sensitivity of the SHI, we calculate the average of one-day acceleration so that

$$a = \text{EMA}(14) \text{ of } a_t$$

The price displacement y is equal to $(C - C_y)$; therefore, the one-day period T is expressed by

$$T = 2\pi\sqrt{\frac{y}{a}} \quad \text{or} \quad T = 6.28\sqrt{\left|\frac{(C - C_y)}{\text{EMA}_{14}\,[(C - C_y) - (C_y - C_{by})]}\right|}$$

When y has a negative value, the period should have a negative value by its turn. However, when both y and a have negative signs, the period will yield a positive value indicating a buying strength. To prevent such a discrepancy, an absolute value is taken for the above equation. In this article, we will consider y is equal to $(\text{price}_{today} - \text{price}_{yesterday})$ instead of (today's price). The reason for this change is that the SHI should not easily reach its extreme levels during uptrends and downtrends. The change in price will reduce the values of the oscillator to prevent the SHI line from crossing the extreme levels frequently. If C is greater than C_y, then T is given a positive sign. If C is less than C_y, then T is given a negative sign. Finally,

$$\text{SHI} = \text{EMA}(14) \text{ of } T$$

Trading Tactic

The trading tactic used for the simple harmonic index is merely the centerline crossover. A buy signal is generated when the SHI line moves above the zero level to turn positive. The period of the bull cycle rises, leading to an increase in price displacement. A sell signal is generated when the SHI line crosses down the centerline to turn negative. Figures 26 and 27 demonstrate the signals of the oscillator.

Figure 26. Centerline crossover signals of the SHI

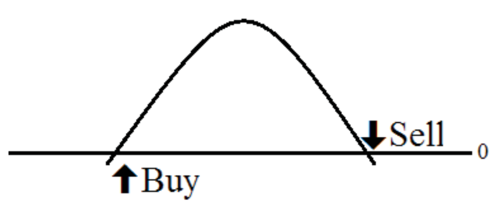
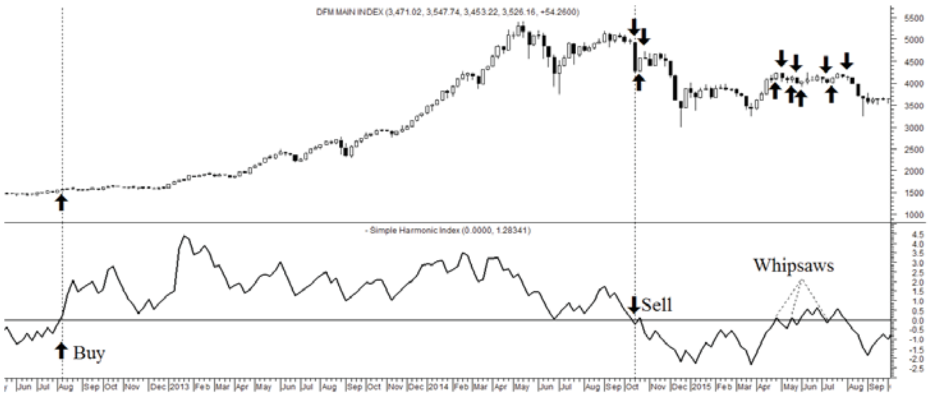


Figure 27. Dubai financial market—Weekly values of Dubai General Index (.DFMGI)



Support and Resistance Analysis

Like the price, SHI forms highs and lows that can be connected to each other and creates support and resistance lines. Sometimes the SHI breaks its support or resistance earlier. This behavior can be used as a leading move indicating that the price support or resistance will be broken during the following phase. In Figure 28, the SHI has broken its support before the price breakout.

Figure 28. Egyptian Stock Exchange—Daily Values of Al Ahly Development (AFDI.CA)

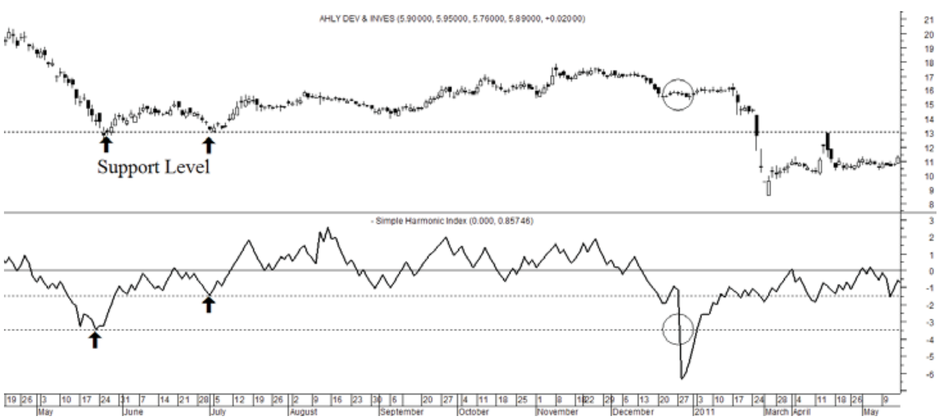
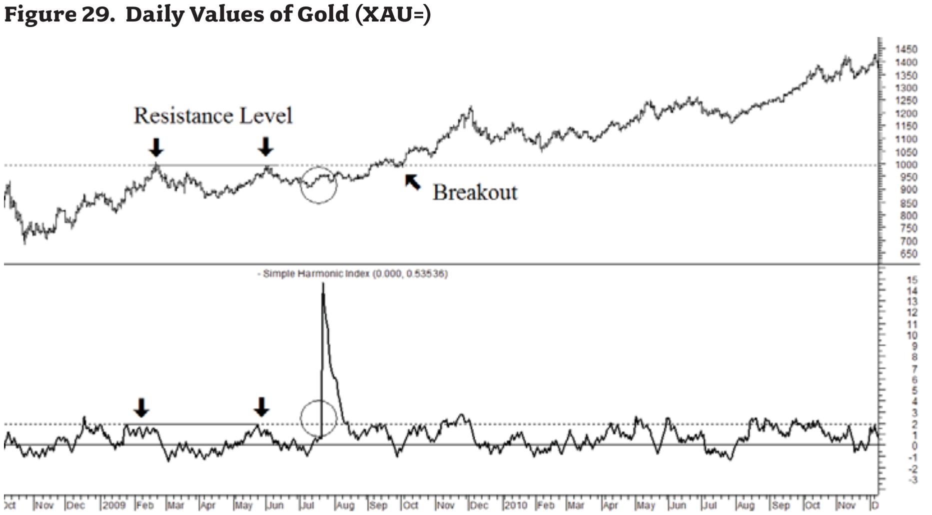


Figure 29. Daily Values of Gold (XAU=)



Divergences

Like the WPO, the simple harmonic index exhibits divergences with price. Figures 30 and 31 demonstrate an example of the SHI divergence.

Figure 30. NYMEX—Weekly Values of Light Crude Oil (CLc1)

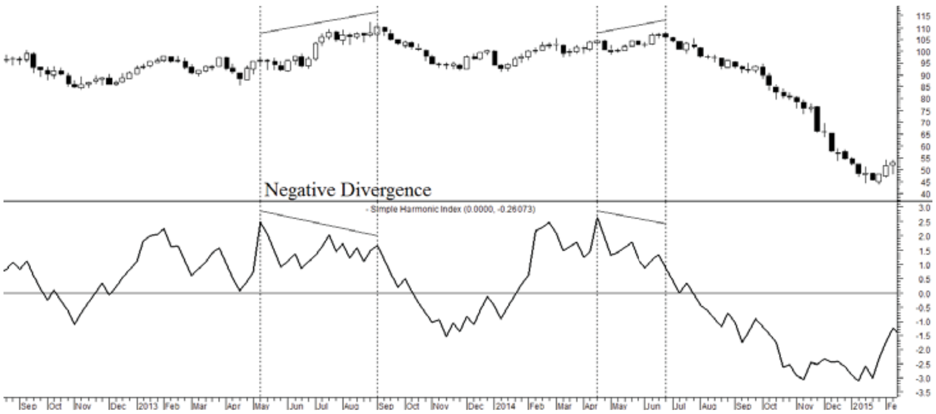
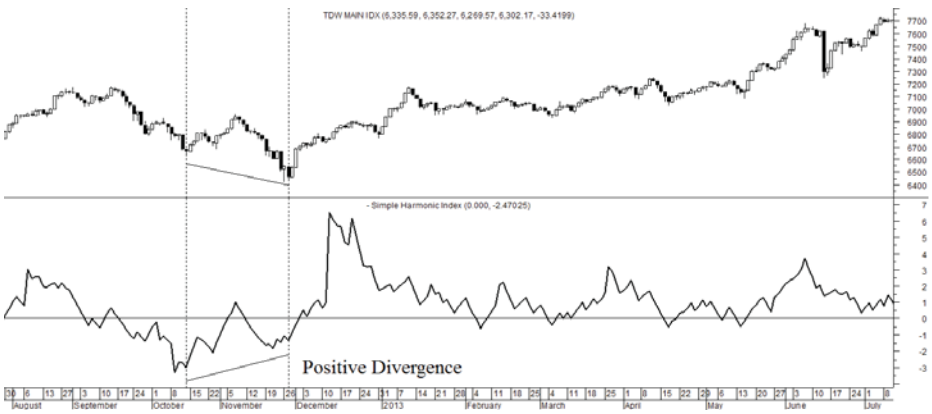


Figure 31. Saudi Stock Exchange—Daily Values of Tadawul Main Index (.TASI)



Simple Harmonic Oscillator (SHO)

Structure

The SHO is a bounded oscillator for the simple harmonic index that calculates the period of the market's cycle. The oscillator is used for short and intermediate terms and moves within a range of -100 to 100 percent. The SHO has overbought and oversold levels at +40 and -40, respectively. At extreme periods, the oscillator may reach the levels of +60 and -60. The zero level demonstrates an equilibrium between the periods of bulls and bears. The SHO oscillates between +40 and -40. The crossover at those levels creates buy and sell signals. In an uptrend, the SHO fluctuates between 0 and +40 where the bulls are controlling the market. On the contrary, the SHO fluctuates between 0 and -40 during downtrends where the bears control the market. Reaching the extreme level -60 in an uptrend is a sign of weakness. Mostly, the oscillator will retrace from its centerline rather than the upper boundary +40. On the other hand, reaching +60 in a downtrend is a sign of strength and the oscillator will not be able to reach its lower boundary -40.

Calculation

The SHO calculation consists of two main parts: The variable period VP and the total period TP. The variable period is equal to the SHI value, and the total period is equal to the exponential moving average of a one-day period. Consider the following equation:

$$T = 6.28\sqrt{\left|\frac{(C - C_y)}{EMA_{14}\,[(C - C_y) - (C_y - C_{by})]}\right|}$$

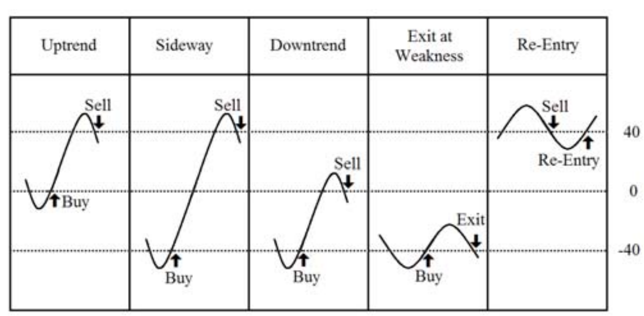
Following the steps below:

- Ti = +T if C > Cy
- Ti = -T if C < Cy
- VP = EMA (14) of Ti
- TP = EMA (14) of T
- $SHO = \frac{VP}{TP} \times 100$

Trading Tactics

Like the wave period oscillator, the SHO trading tactics consist of uptrend, sideway, downtrend, exit at weakness, and re-entry tactics as shown in Figure 33.

Figure 33. SHO signals during trends

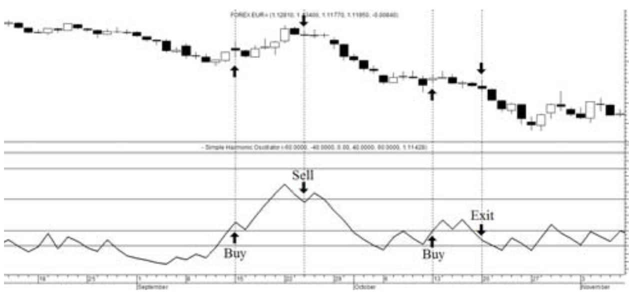


Examples of SHO Signals: Figures 34, 35, and 36 demonstrate the signals generated by the SHO during uptrend, sideways, and downtrend, respectively.

Figure 34. Egyptian Stock Exchange—Daily Values of Pioneers Holding (PIOH.CA)

Figure 35. Egyptian Stock Exchange—Daily Values of EFG Hermes Holding (HRHO.CA)

Figure 36. Daily Values of Euro-Dollar (EUR=)

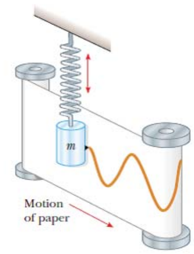


Periods Precede Volumes

Mathematical Approach

Periods precede volumes is based on Hooke's law, named after the British physicist Robert Hooke. Hooke's law finds the relation between the period and the mass of oscillating bodies. In Figure 37, a body with mass m is attached to a spring moving only in upward and downward directions. A marker is attached to the body to trace its motion on a rolling paper, which moves in the right direction, perpendicular to the motion of the body. As a result, the marker attached to the oscillating body traces out a sinusoidal pattern on the moving chart paper.

Figure 37. An experimental apparatus demonstrating the simple harmonic motion (adapted from *Physics for Scientists and Engineers* 2004, p. 456)



Such a mechanism exists in the price movement. The closing price of one weekly bar rises or falls during the week. However, we see it as a sinusoidal line on the daily timeframe. The daily time axis moves only to the right from present to future like the motion of the paper. Figure 38 demonstrates the closing price of one weekly bar with equal increments during the week. The first day starts at 20, then the price changes each day by +10 and -10.

Figure 38. The relation between the closing price levels of one weekly bar and the daily closing prices for the same week

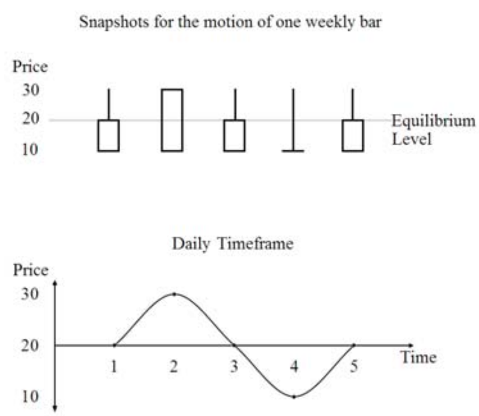
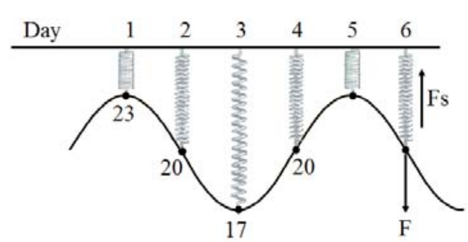


Figure 39. Example of applied forces on oscillating price



In Figure 39, the price at any day is considered a moving body with mass m. The stock's volume is considered the mass of the "price body," which will not exist if the volume is equal to zero (no trade). Let us assume that the price body is attached to a spring. When the spring is neither stretched nor compressed, the price becomes at the equilibrium position of the system which we identify at 20. On the third day, the price moves down by 3 units to close at 17. The spring stretches down and builds a restoring force Fs trying to pull back the price body to its equilibrium position again. In this example, the market force F refers to the dominant sellers while Fs refers to the resisting buyers during the first three days.

According to Hooke's law, the force of the spring is

$$F_s = -k.y$$

where k is called the spring constant. The negative sign indicates that Fs is in the opposite direction of the force F, where F is the product of mass and acceleration. According to Hooke law, F = Fs. Therefore,

$$m.a = -\,k.y$$

Therefore,

$$k = \frac{-\,m.a}{y}$$

As derived earlier, ω^2 is equal to (- a/y). Consequently, the angular frequency

$$\omega = 2\pi f = \sqrt{\frac{k}{m}}$$

And the wave period

$$T = 2\pi\sqrt{\frac{m}{k}}$$

By applying the above equation on prices, the one day period will be equal to

$$\text{T of today} = 6.28\sqrt{\frac{\text{volume of today}}{\text{k of today}}}$$

When the value of the spring constant *k* rises or falls, the period will be considered as the change in volume, therefore, the periods will lead volumes by phase.

Examples of Leading Periods

The following examples include a comparison between the 14-day exponential moving averages of volumes, wave periods, and simple harmonic periods.

Figure 40. Egyptian Stock Exchange—Daily Values of Heliopolis Housing (HELI.CA)

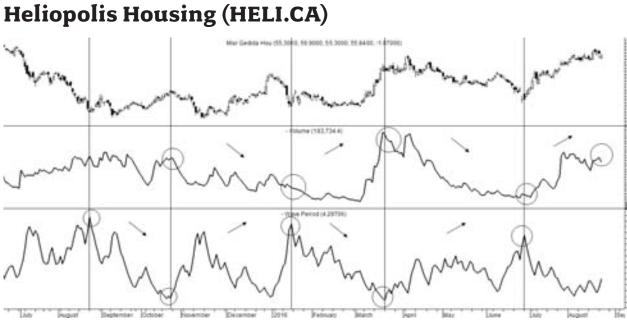
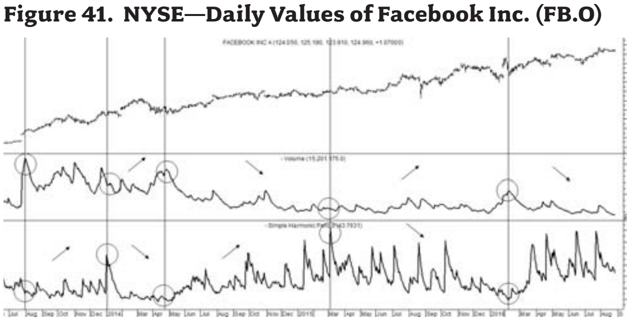


Figure 41. NYSE—Daily Values of Facebook Inc. (FB.O)



In Figure 41, the major peaks of volumes and periods are used to define the phases. During the first phase, the period indicator starts to rise until January 2014. During the second phase, the volume rises by its turn until mid-April. Simultaneously, the period falls leading to a decline in volumes within the third phase from mid-April 2014 to March 2015.

Figure 42. Egyptian Stock Exchange — Daily Values of Arab Cotton Ginning (ACGC.CA)

Figure 42 above demonstrates a comparison between the SHO and the volume zone oscillator (VZO) created by Waleed Khalil. "*Volume Precedes Price* is the conceptual idea for the VZO" (Khalil 2009, p.18). During phases A and B, the SHO rises to approach the upper boundary driving the VZO to fluctuate between its centerline and the extreme upper boundary in phase C. The behavior of the VZO indicates an increase in the average volume leading to price rally. In phase D, the SHO fails to reach the upper boundary showing a weakness in the average period of buyers. Hence, the pull back of the SHO confirms the importance of the sell signal generated by the VZO. The positive divergence between the SHO and the VZO has led the latter to move from the extreme oversold level to its centerline while confirming the importance of the VZO buy signal at -40.

Testing Results

Centerline Crossover Tactic

This tactic is tested during uptrends. The buy signals are generated when the WPO/SHI cross their centerlines to the upside. The sell signals are generated when the WPO/SHI cross down their centerlines. To define the uptrend in the system, stocks closing above their 50-day EMA are considered while the ADX is above 18.

Uptrend Tactic

During uptrends, the bulls control the markets, and the oscillators will move above their centerline with an increase in the period of cycles. The lower boundaries and equilibrium line crossovers generate buy signals, while crossing the upper boundaries will generate sell signals. The "Re-entry" and "Exit at weakness" tactics are combined with the uptrend tactic. Consequently, we will have three buy signals and two sell signals.

Sideways Tactic

During sideways, the oscillators fluctuate between their upper and lower boundaries. Crossing the lower boundary to the upside will generate a buy signal. On the other hand, crossing the upper boundary to the downside will generate a sell signal. When the bears take control, the oscillators will cross down the lower boundaries, triggering exit signals. Therefore, this tactic will consist of one buy signal and two sell signals. The sideway tactic is defined when stocks close above their 50-day EMA and the ADX is below 18.

Downtrend Tactic

During downtrends, the bears control the markets and the time cycle oscillators will move below their centerline with an increase in the period of cycles when the downtrend runs with high momentum. The lower boundary crossovers generate buy signals, while crossing the centerline to the downside will generate sell signals. The "Exit at weakness" tactic is combined with the downtrend tactic. Consequently, we will have one buy signal and two sell signals. To define the downtrend in the system, stocks closing below their 50-day EMA are considered while the ADX is above 18.

Table 3. WPO testing results for 10 years in Egyptian Stock Market

Egyptian Stock Exchange 1/1/2006–1/1/2016				
Tactics	Centerline Crossover	Uptrend	Sideways	Downtrend
Net Profit %	3412.13%	1120.32%	192.77%	88.11%
Exposure %	38.28%	69.34%	51.31%	44.35%
Net Risk Adjusted Return %	8913.92%	1615.80%	375.71%	198.68%
Annual Return %	42.74%	28.42%	11.34%	6.52%
Risk Adjusted Return %	111.66%	41.00%	22.10%	14.71%
All trades	11288	5595	2483	7000
Avg. Profit/Loss %	1.47%	2.57%	3.09%	0.63%
Avg. Bars Held	5.2	18.23	25.15	6.73
Winners	3190 (28.26 %)	2118 (37.86 %)	948 (38.18 %)	2436 (34.80 %)
Total Profit	700,848.29	558,711.93	113,355.23	91,946.53
Avg. Profit %	10.68%	17.45%	20.29%	9.22%
Avg. Bars Held	10.58	24.24	32.52	9.59
Largest win	16,675.66	13,579.46	2,894.75	1,953.35
# bars in largest win	54	29	12	12
Losers	8098 (71.74 %)	3477 (62.14 %)	1535 (61.82 %)	4564 (65.20 %)
Total Loss	-359,634.88	-446,679.67	-94,077.96	-83,135.40
Avg. Loss %	-2.16%	-6.49%	-7.53%	-3.95%
Avg. Bars Held	3.08	14.57	20.59	5.2
Largest loss	-3,677.90	-3,009.85	-821.16	-338.04
# bars in largest loss	2	19	17	19
Max. trade drawdown	-3,677.90	-3,452.86	-1,636.79	-628.24
Max. system % drawdown	-17.18%	-50.91%	-41.69%	-56.96%
Profit Factor	1.95	1.25	1.2	1.11
Payoff Ratio	4.95	2.05	1.95	2.07
Risk-Reward Ratio	1.34	0.41	0.31	0.08

Table 4. SHI testing results for 10 years in Egyptian Stock Market

Egyptian Stock Exchange 1/1/2006–1/1/2016	
Tactics	Centerline Crossover
Net Profit %	1500.85%
Exposure %	48.55%
Net Risk Adjusted Return %	3091.55%
Annual Return %	31.96%
Risk Adjusted Return %	65.83%
All trades	6725
Avg. Profit/Loss %	1.82%
Avg. Bars Held	9.29
Winners	1674 (24.89 %)
Total Profit	352,087.87
Avg. Profit %	16.12%
Avg. Bars Held	22.94
Largest win	13564.3
# bars in largest win	17
Losers	5051 (75.11 %)
Total Loss	-202,002.98
Avg. Loss %	-2.92%
Avg. Bars Held	4.77
Largest loss	-1864.7
# bars in largest loss	12
Max. trade drawdown	-3772.65
Max. system % drawdown	-23.41%
Profit Factor	1.74
Payoff Ratio	5.26
Risk-Reward Ratio	1.39

Table 5. SHO testing results for 10 years in Egyptian Stock Market

Egyptian Stock Exchange 1/1/2006–1/1/2016			
Tactics	**Uptrend**	**Sideways**	**Downtrend**
Net Profit %	2759.79%	242.00%	236.64%
Exposure %	52.48%	35.61%	41.33%
Net Risk Adjusted Return %	5258.95%	679.66%	572.54%
Annual Return %	39.84%	13.08%	12.91%
Risk Adjusted Return %	75.92%	36.75%	31.23%
All trades	9984	2749	8164
Avg. Profit/Loss %	1.65%	2.31%	0.70%
Avg. Bars Held	9.92	15.94	6.23
Winners	3603 (36.09 %)	1154 (41.98 %)	2621 (32.10 %)
Total Profit	1,009,423.53	105,133.15	113,352.45
Avg. Profit %	12.33%	14.63%	9.09%
Avg. Bars Held	14.31	18.73	9.96
Largest win	38824.65	2,861.13	1,951.49
# bars in largest win	26	8	13
Losers	6381 (63.91 %)	1595 (58.02 %)	5543 (67.90 %)
Total Loss	-733,444.11	-80,932.75	-89,688.82
Avg. Loss %	-4.39%	-6.61%	-3.26%
Avg. Bars Held	7.44	13.93	4.47
Largest loss	-4009.91	-955.32	-419.02
# bars in largest loss	8	14	6
Max. trade drawdown	-4366.96	-2,800.69	-727.82
Max. system % drawdown	-34.48%	-35.95%	-48.08%
Profit Factor	1.38	1.3	1.26
Payoff Ratio	2.44	1.8	2.67
Risk-Reward Ratio	0.73	0.38	0.73

Conclusion

Time cycle oscillators give an insight about the relation between time, volume, and price movements. In this article, we used the oscillators to differentiate between the time taken by bulls and bears to complete one cycle.

Advantages of the time cycle oscillators

- The time cycle indicators can replace the volume data in FX market.
- The irregular cycle lines generated by the WPO analyze the volatility of markets.
- SHO has fewer whipsaws than the WPO on their equilibrium lines.
- Both SHO and WPO can be used simultaneously to minimize their whipsaws.
- The cycle period, calculated by the SHI and SHO, is independent of the amplitude and the phase constant.

Disadvantages of the time cycle oscillators

- The oscillators are not based on the forced and damped oscillations concepts which take into account the change in amplitude during the day.

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Software and Data

Testing was performed by AmiBroker software.

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

Appendix

Indicator Codes

Indicators	Metastock	Amibroker

Wave Period Oscillator (WPO)	n:=14;
	Cy:= Ref(C,-1);
	A:= H;
	sinwt:= C/A;
	sinsq:= Power(sinwt, 2);
	cossq:= 1-(sinsq);
	coswt:= Sqrt(cossq);
	Angle:= atan(sinwt,coswt);
	Rad:= 3.14*Angle/180;
	Tt:= 6.28/Rad;
	Ti:= If(C > Cy, Tt, -Tt);
	WPO:= Mov(Ti,n,E);
	WPO
		n = 14;
		Cy = Ref(C,-1);
		A = H;
		sinwt = C/A;
		Angle = asin(sinwt);
		Tt = 6.28/Angle;
		Ti = iif(C > Cy,Tt,-Tt);
		WPO = EMA(Ti,n);

Simple Harmonic Index (SHI)	n:=14;
	Cy:= Ref(C,-1);
	vt:= C-Cy;
	vy:= Ref(vt,-1);
	at:= vt-vy;
	a:= Mov(at,n,E);
	d:= C-Cy;
	Tt:= Sqrt(Abs(d/a));
	Ti:= If(C>Cy,Tt,-Tt);
	SHI:= Mov(Ti,n,E);
	SHI
		n= 14;
		Cy= Ref(C,-1);
		vt= C-Cy;
		vy= Ref(vt,-1);
		at= vt-vy;
		a= EMA(at,n);
		d= C-Cy;
		Tt= Sqrt(Abs(d/a));
		Ti= iif(C>Cy,Tt,-Tt);
		SHI= EMA(Ti,n);

Simple Harmonic Oscillator (SHO)	n:=14;
	Cy:= Ref(C,-1);
	vt:= C-Cy;
	vy:= Ref(vt,-1);
	at:= vt-vy;
	a:= Mov(at,n,E);
	d:= C-Cy;
	Tt:= Sqrt(Abs(d/a));
	Ti:= If(C>Cy,Tt,-Tt);
	VP:= Mov(Ti,n,E);
	TP:= Mov(Tt,n,E);
	SHO:= VP/TP*100;
	SHO
		n=14;
		Cy= Ref(C,-1);
		vt= C-Cy;
		vy= Ref(vt,-1);
		at= vt-vy;
		a= EMA(at,n);
		d= C-Cy;
		Tt= Sqrt(Abs(d/a));
		Ti= iif(C>Cy,Tt,-Tt);
		VP= EMA(Ti,n);
		TP= EMA(Tt,n);
		SHO= VP/TP*100;

Key Performance Indicator

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Abstract

A key performance indicator with high explanatory value for the quality of trading systems is introduced. Quality is expressed as an indicator and comprises the individual values of qualitative aspects. The work developing the KPI was submitted for the 2017 VTAD Award and won first prize.

Introduction

Imagine that you have a variety of stock trading systems from which to select. During backtesting, each trading system will deliver different results with regard to its indicators (depending on, inter alia, its parameters and the stock used). You will also get different forms of progression for profit development. It requires great experience to select the "best" trading system from this variety of information (provided by several indicators) and significantly varying equity progression forms.

In this paper, an indicator will be introduced that expresses the quality of a trading system in just one figure. With such an indicator, you can view the results of one backtest at a glance and also more easily compare a variety of backtesting results with one another.

Profit Development Progression

As an example, Figure 1 shows the results of backtesting for one trading system. A total of six items were carried out for one DAX share. Among other things, the diagram shows profit development as an equity progression (closed equity). For items with profit not yet realised, (open) equity is also displayed (blue line).

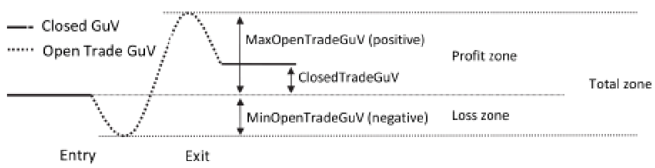
Figure 1. Results of backtesting for one trading system

During the formation of the key performance indicator (KPI), equity progression was analysed following different areas of focus. Within these areas of focus, aspect values are determined for qualitative statements. These are relative numeric values, whereby 1.0 stands for the highest qualitative statement.

Focus: Open Profit/Loss

Within an open item, the profit or loss (GuV) not yet realised (OpenTradeGuV) reaches a maximum (MaxOpenTradeGuV) and minimum value (MinOpenTradeGuV). After one item is closed out, these values become known.

Figure 2. Division of zones of open GuV within one position



From profit or loss realised (GuV) for one closed item (ClosedTradeGuV) and the minimum and maximum values found, conclusions can be drawn for behaviour during the execution of one item.

In our example system, the following values were reached:

Table 1. Minimum and maximum values found for open items in the example trading system

Item (Index)	ClosedTradeGuV [EUR]	MinOpenTrade-GuV [EUR]	MaxOpenTrade-GuV [EUR]
Item 1	4,874.00	-126.00	7,368.00
Item 2	-719.25	-679.25	250.25
Item 3	1,196.60	-610.20	2,608.20
Item 4	-1,562.85	-2,054.85	106.40
Item 5	-604.20	-1,051.05	236.60
Item 6.	877.70	-131.10	3,944.40
Total	4,062.00	-4,652.45	14,513.85

Aspect: Profit-Taking Efficiency

The aspect of "profit-taking efficiency" concerns the relationship between ClosedTradeGuV and MaxOpenTradeGuV. How large is the proportion of realised GuV in comparison to the maximum GuV reached (but not realised) for the item?

A higher profit-taking efficiency value indicates a higher quality for the item. This is because the more possible profit was realised for the position, the better the exit from the item was executed. Profit taking thus occurs to the highest degree of efficiency possible. Profit-taking efficiency values allow conclusions to be drawn for the exit strategy used.

In the example, a maximum non-realised profit of EUR 7,368 is reached for the displayed Item 1, and it is closed with EUR 4,874. Profit-taking efficiency for this item therefore amounts to 66% (0.66=4,874/7,348). A higher profit would thus have been possible for this item.

All items in the system are analysed for an aspect value. This means that this value provides information on how effective profit taking was on average:

$$ProfitTakingSystemEfficiency = \frac{SystemGuV}{\sum_{p=1}^{n} MaxOpenTradeGuV(p)}$$

For our system, this value is calculated as follows:

$$ProfitTakingSystemEfficiency = \frac{4{,}062.00EUR}{14{,}513.85EUR} = 0.28$$

Profit taking thus occurs at an average level of 28%.

Aspect: Open Profit/Loss Ratio

This aspect concerns the proportion of OpenTradeGuV within the profit zone compared to the overall zone. The aspect shows how large the maximum possible profit is in relation to the maximum possible loss.

A higher value in the open profit/loss ratio indicates a higher quality for the item. The more non-realised GuV progresses in the profit zone, the better the entry in the item. There were thus better chances for a profitable exit.

Values in the open profit/loss ratio therefore allow conclusions to be drawn for the entry strategy. In the example, a minimum value of EUR -610.20 and a maximum value of EUR 2,608.20 were reached for Item 3. 81% of Open GuV therefore progressed within the profit zone (0.8=2,608.20/(2,608.20+610.20)). There were thus increased chances of a profitable exit for this item.

All items in the system are analysed for an aspect value:

$$OpenProfitLossSystemRatio = \frac{\sum_{p=1}^{n} MaxOpenTradeGuV(p)}{\sum_{p=1}^{n} MaxOpenTradeGuV(p) - \sum_{p=1}^{n} MinOpenTradeGuV(p)}$$

This value therefore provides the information on what proportion of open GuV progressed within the profit zone in total.

For our system, this value is calculated as follows:

$$OpenProfitLossSystemRatio = \frac{14{,}513.85EUR}{14{,}513.85EUR - (-4{,}652.45EUR)} = 0.76$$

76% of open equity was therefore within the profit zone. This means that a majority of open equity progressed within the profit zone.

Focus: Profit Increase

Profits and an increasing equity progression are expected of a trading system. This requires items that cause higher highs for equity (title: MaxDrawUp). In Figure 1, the current highest equity is marked as a striped line.

Aspect: MaxDrawup Density

The aspect now introduced is concerned with the equal presence of items causing a new MaxDrawup. In Figure 1, these are marked as HE items (HE stands for Highest Equity). Should equity increases be equally distributed among all occurring items, this indicates a higher quality. This is because when profit increases are found in an equal distribution, the probability of further profit increases in similar equal distributions increases. As a result, trust in the trading system increases.

The equal distribution of the occurrence is determined using a density value. This includes a comparison with an assumed ideal distribution of IHE items (I stands for ideal) For the first HE item, the first IHE item therefore represents its ideal position.

The following table shows real and theoretical ideal distribution of the items individually in MaxDrawUp:

Table 2. Profit progression of the example trading system

Item (Index)	Equity [EUR]	Real Distribution	Assumed Theoretical Ideal Distribution	Absolute Distances between Ideal and Real Distribution
Item 1	4,874.00	HE(1)=1		
Item 2	4,154.75			
Item 3	5,351.35	HE(2)=3	IHE(1)=3	2 (Distance to Item 1)
Item 4	3,788.50			
Item 5	3,184.30			
Item 6	4,062.00		IHE(2)=6	3 (Distance to Item 3)
Total				5

For a theoretical ideal distribution, the distance between two IHE items is first determined. This is found by dividing the number of all items by the number of IHE items. For the example, this figure is 6/2 = 3.

For each ideal item, the absolute distance to the corresponding real item is determined. In the example of the second item, this is: |IHE(2) – HE(2)| = |6 – 3| = 3. Thus, the closer an HE item is located to its ideal position, the lower its absolute distance.

To reach relative density values, the absolute distances are divided by the number of all items, thereby standardising them. In the example of the second item, this is 3/6. This means the distance between an HE item and its ideal position is 1 at the most.

To form a mean deviation, the standardised absolute distances are added (2/6+3/6=5/6) and divided by the number of HE items (=5/12). The more the distribution of HE items approaches the theoretical ideal distribution, the less the value of mean deviation. Upon complete ideal distribution, it amounts to 0.

For the calculation of a density value for which 1 stands for the highest qualitative statement, the value of mean deviation is subtracted from 1. In our example, we receive 0.58=1-5/12.

The closer the density value is to 1.0, the closer its proximity to idea distribution.

MaxDrawup density can be calculated using the following formula:

$$MaxDrawupDensity = 1 - \frac{\sum_{p=1}^{n} |\, IndexIHE(p) - IndexHE(p)|}{mn}$$

m – total number of items,
n – number of items causing a new equity high
IndexIHE(p) equals the index of the ideal theoretical HighestEquity item for p
IndexHE(p) equals the index of the real HighestEquity item for p

In our example, we use:

$$MaxDrawupDensity = 1 - \frac{|3-1| + |6-3|}{6 * 2} = 0.58$$

Focus: Maximum Drawdowns

This focus is concerned with decline in profit occurring after a new equity high. The largest decline in profit after a new equity high corresponds to maximum drawdown.

Aspect: MaxDrawup/MaxDrawdown Ratio

The following aspect describes the ratio between maximum drawdown and its last increase in profit. From a perspective of quality, it is assumed that maximum drawdown should be kept as low as possible relative to profit increase. The lower the maximum drawdown within one profit increase, the better the quality aspect.

Figure 3 shows an example sketch of a closed equity progression between two items, each of which causes a new equity high (HE stands for Highest Equity)

A new drawdown causing the largest distance to the last high forms the respective current OpenMax-Drawdown from the last high. Upon reaching a new equity high, in Diagram HE(2), the final maximum drawdown after HE(1) has been reached can be calculated. This is called ClosedMax-Drawdown. In Figure 1, these are referred to as OMDD and CMDD.

Table 3 shows the increases for each highest instance of equity occurring in our example system and the maximum drawdowns.

Table 3. Drawdowns calculated for the example trading system

Item (Index)	Equity [EUR]	Highest Equity [EUR]	Profit Increase of the Highest Equity [EUR]	Drawdown [EUR]
Item 1	4874,00	4874,00	4874,00	
Item 2	4154,75	4874,00		719,25
Item 3	5351,35	5331,35	457,35	
Item 4	3788,50	5331,35		1562,85
Item 5	3184,30	5331,35		2167,05
Item 6	4062,00	5331,35		1289,35

Since a new equity high was reached with Item 3, the decline in profit from the high of EUR 4,874.00 can be determined with EUR 719.25 as ClosedMax-Drawdown. With Item 3, the last equity high was reached. The largest decline in profit after this item is therefore considered an OpenMax-Drawdown. This was reached with Item 5 at EUR 2,167.05.

With Item 3, an equity profit increase of EUR 457.35 occurs. Maximum drawdown of a total of EUR 2,162.05 is very high compared to profit increase. This produces a ratio of 0.17 (=457.35/(457.35 + 2,167.05)).

For an aspect value, a ratio is calculated between the total sum of all maximum drawdowns and the maximum profit increase.

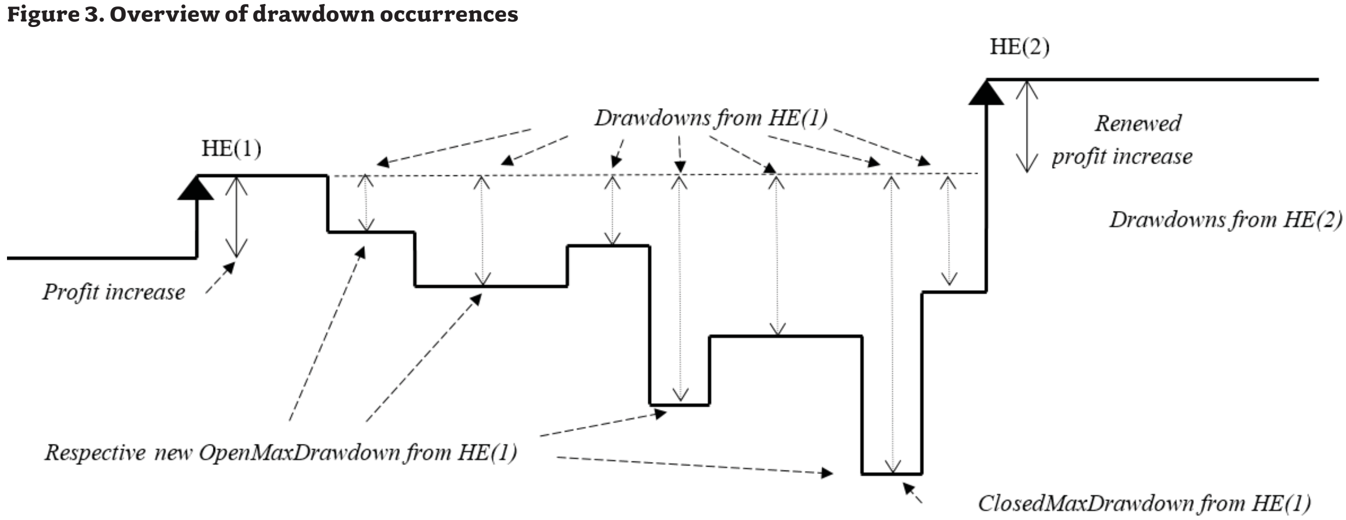
$$MaxDrawupDrawdownRatio = \frac{HighestEquity}{HighestEquity + \sum_{p=1}^{n-1} ClosedMaxDrawdown(p) + OpenMaxDrawdown(n)}$$

Our example trading system produces a value of 0.65:

$$MaxDrawupDrawdownRatio = \frac{5{,}331.35EUR}{5{,}331.35EUR + 719.25EUR + 2{,}167.05EUR} = 0.65$$

If no drawdowns at all are ideally generated in a trading system, this produces a value of 1.0. With increasing drawdowns, this value approaches zero.

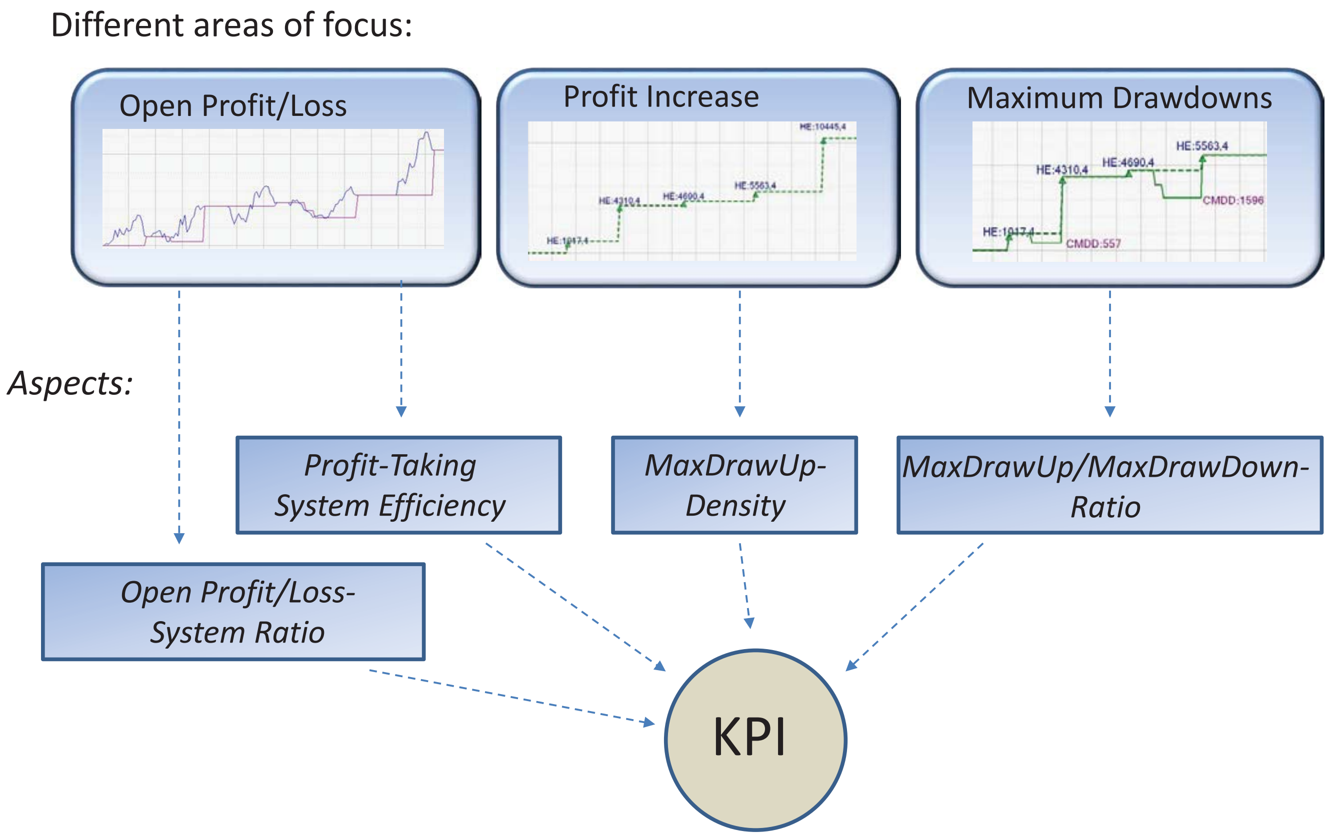
Figure 3. Overview of drawdown occurrences



Formation of a Combined Indicator

Figure 4 shows the composition of the key performance indicator.

Figure 4. Composition of KPI



To form an indicator, the results of the qualitative aspects with equal weighting are totalled:

KPI=(ProfitTakingSystemEfficiency+OpenProfitLossSystemRatio +MaxDrawupDensity+MaxDrawupDrawdownRatio)/4

In our example, the following aspect values were calculated:

Table 4: Calculated individual values of the qualitative aspects of the example trading system

Aspect	Aspect Value
Profit-taking system efficiency	0.28
Open profit/loss system ratio	0.76
MaxDrawup density	0.58
MaxDrawup/Drawdown ratio	0.65

Therefore, our trading system reaches a KPI value of 0.57:

$$KPI = \frac{0.28 + 0.76 + 0.58 + 0.65}{4} = 0.57$$

A KPI value of 1.0 marks a trading system of the highest quality. The low aspect value for profit-taking efficiency calculated in our example indicates an improvement in exit strategy used.

Conclusion

The KPI developed has high explanatory value for the quality of a trading system. Individual aspect values (from different areas of focus) provide further information useful for improving the quality of a trading system. Users can use the KPI value and its aspect values during the development of trading systems. Further, application during parameter optimisation and as a monitoring measure during practical trading is possible. The KPI introduced was implemented in the programming language Equilla and can be used in the trading environment Tradesignal.

The original paper (in German), containing many examples and the programming code, is available on the VTAD website: http://www.vtad.de/node/11524.

Magic Cycles and Where Not to Find Them

Empirical Analysis of Discrete Cycles in Daily Stock Charts

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Abstract

Do magic cycles exist? This question is answered in this article based on the data of significant extreme points in stock and index charts. The results of a statistical analysis show an equal distribution for the length of a cycle. Hence, the probability that a day in the future will be an extreme point is constant and therefore independent from the date. Conclusively, there is no empirical evidence for magic cycles in stock and index charts.

Introduction

A price chart has two dimensions: the price and time axes. Each price value has its unique time stamp. Therefore, any event and any pattern found in the chart with the help of technical analysis methods can be marked with a time stamp, too. Conclusively, the chart's time axis is of particular interest itself. Henceforth, the question arises how the time axis and, in particular, a series of events may be analyzed effectively. Considering the approach taken in other fields, the concept of cycles comes into play. A cycle is a periodic series of events. Due to the discontinuous behavior of financial price charts, it is not surprising that this approach has been used regularly—and still is. For example, Murphy (1999) dealt with cycles in his standard work. He honorably mentioned the work of Edward R. Dewey (1973), "one of the pioneers of cyclic analysis", as well as J.M. Hurst (1970). Following Dewey, there exist specific discrete cycle periods that appear significantly more often. One example he mentioned is the 3,39-year cycle. In the meantime, several other cycles have also been discovered. Worth mentioning are the yearly cycle, the presidential election cycle (four-year cycle), and the so-called π cycle. The latter was stated by M. Armstrong, whose life has given the material for a Hollywood movie.

From an applied perspective, concepts of forecast character are of particular interest, of course. Thus, this article will focus on the concepts of cycles with a priori fixed periods. These periods do not need to be pairwise equal (i.e., cycles with a sequence of periods are possible). Such cycles directly induce forecasts. Indeed, Armstrong had gained his reputation for the prediction of the 1978 crash even though another forecast of his crash of bonds for October 2015 turned out to be wrong.

To this day, the idea of discrete cycle-based forecasts results in heated discussions. On the one hand, there exist several examples of more or less stable discrete cycles in historical data. On the other hand, the causality must be called into question, especially considering long periods.

This article is an empirical study. Its main objective is to clarify the significance question of discrete cycles with the help of statistical methods. The first section is a short introduction to the empirical analysis of cycles. For data acquisition, the automatic 1-2-3 algorithm of Maier-Paape (2015) will be used. It detects all relevant local extreme points for any given chart. Following, all possible (half and full) cycles can be evaluated. Based on the obtained data, the significance question is answered by a statistical analysis in the second section. It will be shown that cycle periods are, in general, equally distributed. This directly denies any idea of particular discrete cycles and leads to the conclusion that no empirical motivation for such cycles could be found.

Basics of cycle analysis

A cycle can be described as "a complete alteration in which a phenomenon attains a maximum and minimum value, returning to a final value equal to the original one." (dictionary.com) It is therefore obvious that a cycle always starts and ends with a local high or low point. This characteristic will be essential for the following evaluation.

Highs and lows specify the clock

A cycle not only starts and ends with an extreme value (high or low) but also has one at half the period. Extreme values in a chart thus specify the clock for possible periods. Figuratively speaking, the extreme values are the pillars around which the cycle is drawn like a red ribbon. Mathematically speaking, the half period is the time difference between two extreme points. In terms,

$$\tau = t_e - t_s \qquad (1)$$

with $t_s < t_e$ being the time values of the starting and ending extreme point, respectively. If the chronology of extreme points is known, all possible cycles can be reconstructed. Due to this fact, an automatic detection of such extreme values in any given chart is necessary and sufficient for the following analysis of cycles.

Automatic 1-2-3

The problem of automatically detecting relevant high and low points for any given chart was solved in 2011 by Maier-Paape and his automatic 1-2-3 algorithm. (Maier-Paape, 2015) This algorithm automatically determines relevant extreme points of any chart. The user can influence the algorithm by setting the relevance level for an extreme value. This is done by choosing a scaling variable for a so-called SAR-process. (Kempen, 2016) Greater scalings lead to more significant movements (i.e., fewer but more relevant extreme values). For this article, the automatic 1-2-3 on the integrated MACD is used for different scalings (Figure 1). With similar setups, the author has already done other statistical analyses. (Kempen, 2016; Brenner and Maier-Paape, 2016)

Figure 1. Relevant extreme values (blue line) found by the automatic 1-2-3 with scaling 1. The example shows the daily chart of the Adidas stock from September 2012 until August 2013.

Empirical cycle analysis

In the paper (Brenner and Maier-Paape, 2016), half periods are evaluated (in a trend setting). For the stocks of S&P 100, it shows that the half periods are roughly log-normally distributed without any discontinuous peaks. Based on this observation there already is no empirical motivation for any discrete periods. However, the results do not falsify a possible significance of such periods. First, only the time difference of two consecutive extreme points was considered in the evaluation. Secondly, the paper used a trend restriction on the data. On the contrary, all possible time differences between two extreme points have to be considered to achieve a comprehensive answer.

Finding significant cycles

The length of one (half) cycle is given with equation (1) by the time difference of two extreme points. The only condition the two extreme points must meet is $t_s < t_e$, i.e. the starting extreme point lies before the ending extreme point in time. Especially, the two extreme points framing the half cycle do not have to be consecutive, but the ending extreme point can be the second or third succeeding or, generally speaking, the *n*-th succeeding extreme point (regarding the opening extreme point in the chart). For n>1 this only implies that for one (half) cycle, several (*n*-1 to be exact) extreme points are within one period. These points then just get ignored. Since the automatic 1-2-3 algorithm yields an alternating sequence of highs and lows, half cycles correspond to odd n while whole cycles correspond to even *n*. This way, all half and whole cycles can be constructed.

i.e.,:

Observation 1 *(Set of possible periods).*
The set of half and whole periods matches the set of all τ *given by*

$$\tau = t_e - t_s$$

with $t_s<t_e$ *being the time values of two different extreme values. For a given chart and numbered time values, i.e. the set of extreme point time values is given by* t_i *for* $1\leq i\leq N$ *(N corresponds to the observed number of extreme values within the chart), the period set is given by all time differences*

$$\tau_{i,n} = t_{i+n} - t_i \qquad (2)$$

with $1\leq i\leq N-n$ *and* $1\leq n<N$.

Therefore, to gather all half and whole periods, the time difference between every *i*-th extreme point and all its possible *n*-th successors has to be calculated and saved. By doing so, for every value the corresponding *n* can be saved, too.

If there exist any particular discrete cycles, the corresponding periods should occur systematically more often than other possible time values. Thus, such cycles would cause clear peaks in the frequency distribution of the periods. Even after considering some noise effects that may lead to not perfectly realized cycles, one can still expect significant deviation from a continuous distribution. The assumption of the existence of discrete cycles, therefore, gets rejected if no such deviation from a continuous distribution is observed.

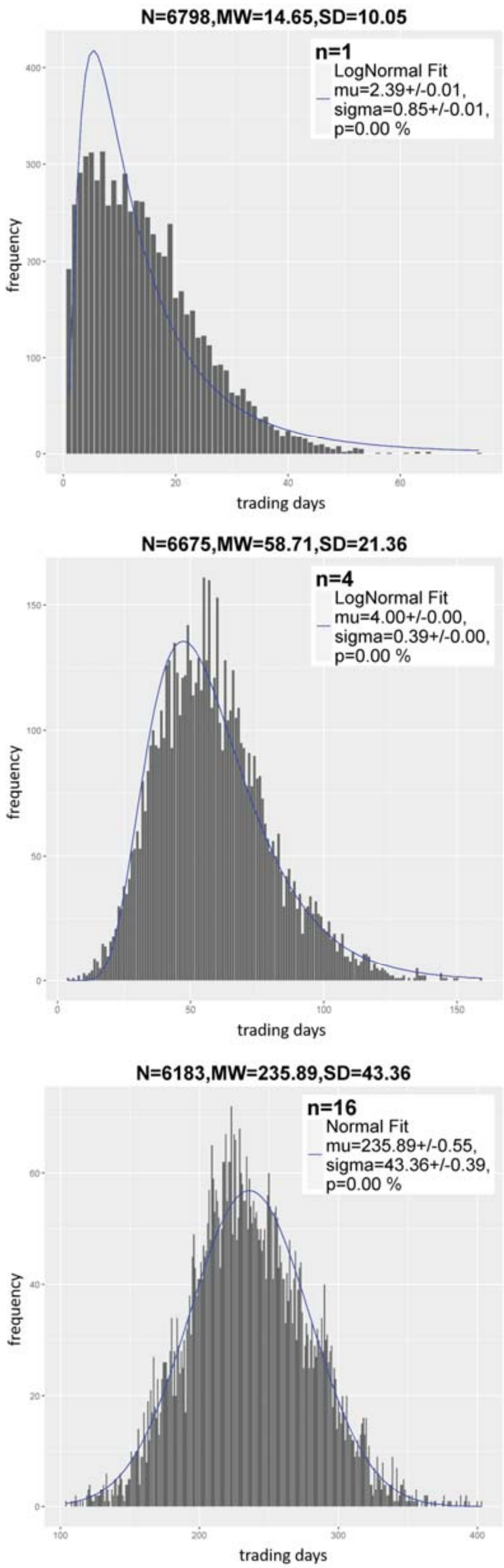
For a comprehensive analysis, different markets are considered at stock and index level. On the one hand, the stocks of the Dax 30, Euro Stoxx 50, S&P 100 and Nasdaq 100 are evaluated. On the other hand, the S&P 100 and 500, Dax 30, Dow 30, Euro Stoxx 50 and Nasdaq 100 are also considered at index level. Besides historical values, data obtained from a geometric Brownian motion (which parameters fit to the Dax 30) is also considered. The simulated data can be used for verifying whether any effects are observed in the historical data. The GBM yields a random market where returns of each day are independently distributed. Thus, there are no significant cycles by definition. All evaluations are done for five different significance levels of the extreme points by running the 1-2-3 algorithm with the scalings 1,1.2,1.5,2 and 3. The obtained data are visualized in histograms, and density curves are applied.

Empirical results

Overall, the results are similar across all markets and scalings. Thus, in the following, the results for different scalings on the stocks of the Euro Stoxx 50 are taken as example for the discussion. All other results can be looked up online at http://www.instmath.rwth-aachen.de/~brenner/files/VTAD2_Anhang.zip.

At first, the distributions of the half and whole cycle periods are considered separately by fixed *n*. Thus, for each evaluation, the considered periods all have the same amount of interior (ignored) extreme points. Namely, there are *n*-1 interior extreme points for a period corresponding to n. For the case *n*=1, the observations made in (2) can be validated also for other markets and without any trend restriction. The frequency distribution of half cycle periods shows log-normal characteristics. The strongest deviation again is within periods between 10 and 35 trading days (Figure 2). In this range, more values have been observed than expected by the log-normal model.

Figure 2. Histogram of (half) periods for *n*=1,4,16 based on the extreme points of the stocks of the Euro Stoxx 50 for scaling 1. The bin size is one trading day.

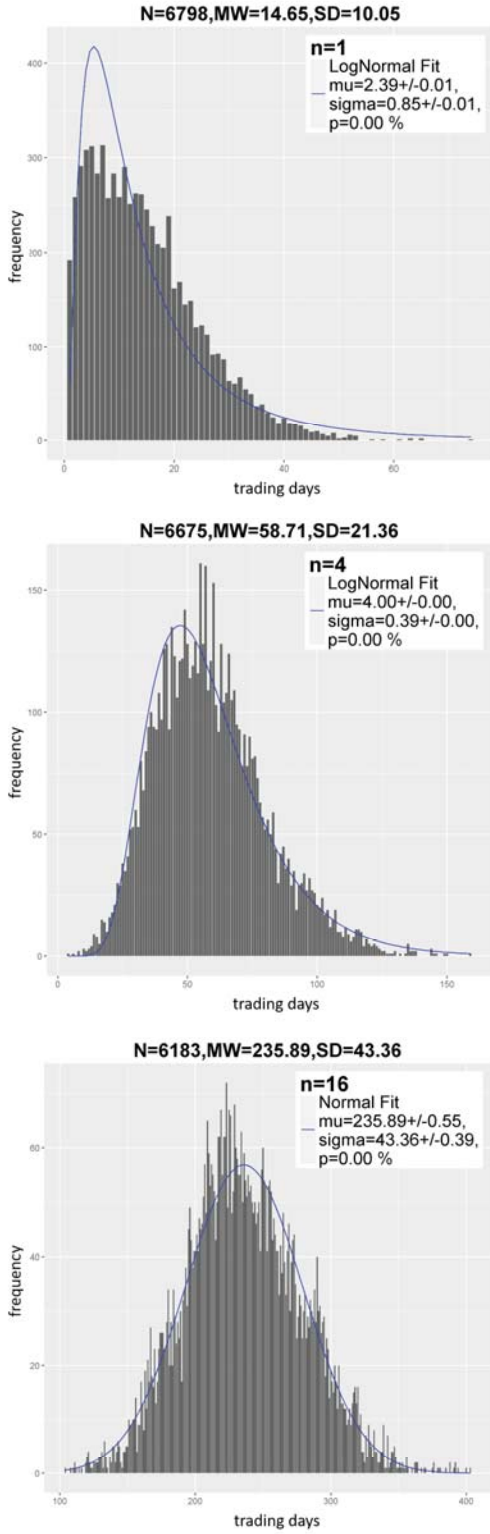


For larger values of *n* (i.e., more highs and lows are ignored within one period), the results show a continuous frequency distribution. Comparing the histograms for increasing *n*, the transformation to a symmetric normal distribution is evident in Figure 2 (*n*=16 with normal fit). This phenomenon could be explained by the central limit theorem, since a period with *n*=16 always is the sum of 16 periods of *n*=1. Assuming that the different n=1 periods are independent and identically distributed, the normal behavior of the sum of these periods follows directly by the central limit theorem for large *n*.

In every single case, namely for all considered markets on stock and index level (see http://www.instmath.rwth-aachen.de/~brenner/files/VTAD2_Anhang.zip), there is no empirical evidence for significant discrete cycles. Of course, this also shows up for the simulated Dax 30 based on the GBM.

For different *n*, the corresponding frequency distributions show different high points. For larger *n*, more iterations between high and low points are within one period. Hence, the mode as well as the mean should increase linearly with *n*. For the question of discrete cycles, the existence of clear high points in the frequency distribution is of special interest. However, this is not a systematic effect but rather of stochastic nature. This becomes clear after comparing the results with those of the simulated market (Figure 3). The frequency distributions for the simulated data show the same characteristics as shown in log-normal model.

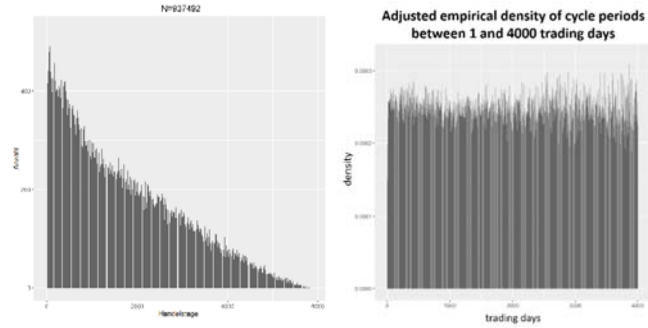
Figure 3. Histogram of (half) periods for *n*=1,4,16 based on the extreme points of the simulated GBM with Dax 30 settings for scaling 1. The bin size is one trading day.



It is evident that some phenomenon that also occurs for a simulated, completely efficient market cannot be exploited and thus does is not suited for any technical analysis argument.

Due to the dependency on n of the frequency distributions, the distribution for all periods independently of *n* is considered eventually. The combination of all frequency histograms is shown in Figure 4 (left).

Figure 4. Unadjusted (left) and adjusted (right) histogram of (half) periods with bin size of one trading day. The linear effect in the left histogram is caused by the limited data history.



The clear linear decay hereby is only caused by the limited data history. Considering a chart with 100 extreme points, there are 99 possible values for periods with *n*=1 since these periods correspond to time differences between two consecutive values, and the last extreme point has no successor. For the case *n*=2, there only are 98 possible periods with the same argument. Conclusively, the number of possible periods decays linearly with n. However, all periods should be considered equally—independent of the corresponding n. For example, a period with *n*=10 is a priori not more frequent than a period with *n*=100. Henceforth, each case has to be readjusted according to its n value such that in total, all cases have equal effect on the outcome. The easiest way to achieve this is to combine the relative frequencies of the different n cases.

An adjusted histogram for values up to 4,000 trading days is shown in Figure 4 (right). It was cut to 4,000 trading days due to the sparse data situation for longer periods, which causes unwanted side effects. The figure shows an equal distribution frequency with some noise. As expected, there are no significant cycles observable.

Conclusion

The conclusion is evident based on the explicit empirical results. For each considered market on stock and index level, there are no such things as discrete cycles. Rather, the periods are a priori equally distributed. Hence, the probability that a day in the future will be an extreme point is constant and therefore independent from the date. Only if there are conditions, like the relevance of the extreme points or the maximal skipped values within one period, is a skewed log-normal like distribution observed. Especially if many extreme values are skipped within one period, this distribution transforms to a symmetric normal distribution due to the central limit theorem. The idea of magic periods therefore cannot be motivated empirically for the considered markets.

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How to Combine Trading Signals

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Abstract

In this work, we investigate how traders can combine several trading signals (e.g., various indicators, opinions of other traders). For this purpose, we transfer evidence theory by Dempster (1967) and Shafer (1967) to trading. We apply the resulting method to social trading, more precisely to copy trading, which means traders copying the portfolios of others.

Introduction

For a given portfolio, all trading strategies basically address the same question: will the prices increase or decrease? They differ with regard to the approach to answer this question. Few traders will rely on their feelings or luck; rather, they will decide based on pieces of information. These can be classified into one of three categories, depending on whether they have been derived from the price histories (technical), assets (fundamental), or behaviour of other traders (social).

Each piece of information can be interpreted as a trading signal—that is, buy (1) or no buy/sell (0). However, it will occur only very rarely that all such signals point in the same direction. Then, the trader needs to combine the contradictory signals to come to a final decision.

Currently, this is usually done heuristically. A simple rule of this kind could be, for example, to buy when two indicators simultaneously reach a critical value region (and, thus, give a signal). One quickly recognises the weaknesses of such a rule: the two indicators are chosen almost arbitrarily, and the remaining signals (e.g., by other indicators) are ignored. Furthermore, the signals' potentially differing reliabilities are not taken into account.

A systematic approach to combine trading signals seems to not yet exist, or at least to not be well known in trading practice. This is somewhat surprising, as the more general problem of combining domain-independent signals has already been studied for several decades (see, e.g., Carl 2001 for an overview of approaches). The purpose of this work, therefore, is to transfer these scientific results to the domain of trading and, while doing so, to extend them in such a way that an analytical basis for the combination of trading signals can be derived from them.

Evidence Theory in Trading

The basic question of each trading strategy mentioned above can be formulated statistically by two mutually excluding hypotheses:

H↑: *The price will increase.*

H↓: *The price will decrease (or stagnate[1]).*

Whether a trader decides to buy or not to buy (or to sell) depends on how much he *believes* in each of these hypotheses. This belief *bel* is influenced by the information the trader has collected. As this information cannot be perfectly certain, the trader's assumptions are vague. For taking into account both factors—his belief and his uncertainty—simultaneously, the standard one-dimensional probability model does not suffice. Dempster (1967) and Shafer (1976), therefore, have developed evidence theory, which extends the probability concept to a two-dimensional measure.

To better understand the novelty of this conception, consider the situation in which a trader who has collected no information so far (this means *bel*(H↑)=0 and *bel*(H↓)=0, as he has no reason to believe in an increase or decrease of the price) asks for the opinion of a trading guru. With a certain probability, say 70%, this guru is reliable. With the complementary probability, here 30%, he is unreliable; however, this does not imply that his prognosis must be wrong! It only means that *nothing is known* about the correctness of his prognosis. If the guru expects a price increase, this will strengthen the trader's belief in H↑: now we have *bel*(H↑)=0.7. At the sime time, *bel*(H↓)=0 remains unchanged because this prognosis does not strengthen the belief in a price decrease.

From the trader's perspective, *bel*(H↑) is a lower limit for the probability that the price will increase. The upper limit, the so called plausibility *pl* of H↑, is given by *pl*(H↑)=1-*bel*(H↓), which in the given example equals 1. The length of the interval [*bel*(H↑);*pl*(H↑)] represents the trader's uncertainty; here, he would estimate the price to increase with a probability between 70% and 100%.

Example of Combining Two Signals

This framework allows us to combine several signals. For a start, we will consider only two. One signaller may again be the aforementioned guru; the other may be a technical indicator with an estimated reliability of, say, 40%. Now four cases are possible; these are specified in Table 1.

Table 1. Possible cases when combining two trading signals

		Signal 2 (e.g., technical indicator)	
		increase	decrease
Signal 1 (e.g., trading guru)	increase	case 1a	case 2a
	decrease	case 2b	case 1b

As the cases 1b and 2b are analogous to the cases 1a and 2a (respectively) with regard to our analysis, it is sufficient to consider only the latter.

Case 1a (analogously 1b, consistent signals):

In case 1a, both signals are consistent because both point to a price increase. Obviously, this should strengthen the trader's belief in H↑ even more (compared to the above example) but have, again, no influence on his belief in H↓ and, thus, the plausibility of H↑. Four new cases have to be distinguished here, this time by whether the two signals are reliable (each) or not (see Table 2).

Table 2. Probability table for the example (bold = normalised values in case 2a)

		Technical indicator	
		reliable (40%)	unreliable (60%)
Trading guru	reliable (70%)	0.7 x 0.4 = 0.28 **0**	0.7 x 0.6 = 0.42 **0.583**
	unreliable (30%)	0.3 x 0.4 = 0.12 **0.167**	0.3 x 0.6 = 0.18 **0.250**

In three of them, at least one signal is reliable, which means that the price will indeed increase. *bel*(H↑) is, therefore, given by *bel*(H↑)=0.28+0.42+0.12=0.82, so that the lower limit of the trader's subjective probability of a price increase is 82% now. As expected, this value is greater than the one in the one-signal situation (70%), while we still have *pl*(H↑)=1 because there again is no evidence for a price decrease. This means that the trader's uncertainty has decreased due to the additional information brought by the technical indicator, as the interval [*bel*(H↑);*pl*(H↑)] has become smaller by 40% (=1-(1-0.82)/(1-0.7)).

Case 2a (analogously 2b, inconsistent signals):

Evidence theory as presented so far may seem plausible but not very innovative. Its actual benefit becomes obvious when signals are inconsistent (i.e., contradict each other). As mentioned above, this will not be the exceptional but rather the regular situation in practice. In our example, it is represented by case 2a, as the technical indicator's prognosis (decrease) here contradicts the guru's (increase).

The probability table for this case is, at first, the same as in case 1a (see again Table 2). However, there is an important difference: When two signals contradict each other, they can no longer both be reliable! The corresponding case, therefore, becomes impossible, so that its occurrence probability (here 0.28) has to be re-distributed among the remaining cases. In other words, the latters' occurrence probabilities have to be scaled in such a way that they add up to 1. The case in which both signals are unreliable, for example, is attributed the new probability 0.18/((0.42+0.12+0.18))=0.25. The remaining values can be seen from Table 2 (printed in bold). The trader will now believe in a price increase only with *bel*(H↑)=0.583 (as this is the new probability with which the guru is reliable), but with *bel*(H↓)=0.167 in a price decrease, as pointed to by the technical indicator! The plausibility of H↑ decreases correspondingly, namely to *pl*(H↑)=1-0.167=0.833, so that the interval for the subjective probability of a price increase now is [0.583;0.833].

The trader's uncertainty is greater here than in case 1a but still lower than in the one-signal situation. This reflects that all signals are valuable, regardless of whether they support or contradict prior assumptions.

Formalisation for Arbitrarily Many Signals

Before we explain how one can make use of *bel*(H↑) and *pl*(H↑) (and the corresponding values for H↓), we first want to extend the calculations presented above only for a concrete example to arbitrary and arbitrarily many signals with arbitrary reliabilities. We refrain from doing so in a mathematically rigorous way—the interested reader is referred to Dempster (1967) and Shafer (1976)—and focus rather on a formalisation through which the method can be applied in practical trading.

Let n be the number of signals that a trader has collected for a certain title. These signals are denoted by $S_1,\dots,S_n$, where S_i takes the value 1 if a signal points to a price increase and the value 0 otherwise. Next, let $r_1,\dots,r_n$ be their reliabilities with $0 \le r_i < 1$, where 1 would mean 100% (i.e., a [hypothetical] perfect signal). We will elaborate on the origin and calculation of these reliabilities later.

Now we proceed in four steps:

1. Consider all possible cases of reliabilities of all n signals. These are exactly 2^n cases; in the above example for n=2, there were 2^2=4. It is helpful to imagine them as sequences of n bits, where the i-th bit takes the value 1 (0) if S_i is (un)reliable. In the above example, the case "The guru is reliable but the indicator is not" would be represented by "10". Let in the following j index one of the 2^n cases, B_j be the corresponding bit sequence, and $B_{j,i}$ denote its i-th bit.
2. For each case j:

   2.1 Calculate its occurrence probability p_j as

$$p_j = \prod_{i=1}^{n} r_i^{B_{j,i}} \cdot (1 - r_i)^{1-B_{j,i}}. \quad (1)$$

   For the aforementioned case represented by "10" in the above example, this evaluates to $p_{"10"} = 0.7^1 \cdot 0.3^0 \cdot 0.4^0 \cdot 0.6^1 = 0.7 \cdot 0.6 = 0.42$ (cf. Table 2).

   2.2 Now four possibilities exist, which we represent through a variable K_j. The first possibility (K_j=1) is trivial; it is given only for the single case in which all signals are assumed to be unreliable (i.e., B_j consists only of zeros). The second and third possibilities are given if *all* signals i that are assumed to be reliable (i.e., for which $B_{j,i}$=1) are consistent (i.e., point in the same direction)—let K_j=2 and K_j=3 represent this for a price increase and decrease, respectively. For most cases, the last possibility is given, in which at least some signals that are assumed to be reliable contradict each other (K_j=4). K_j can be formalised as follows:

$$K_j = \begin{cases} 1 & \text{if } B_{j,i} = 0 \forall i \\ 2 & \text{if } S_i = 1 \forall i | B_{j,i} = 1 \\ 3 & \text{if } S_i = 0 \forall i | B_{j,i} = 1 \\ 4 & \text{otherwise} \end{cases}. \quad (2)$$

   For case 2a in the above example, we have $K_{"00"}=1$, $K_{"10"}=2$, $K_{"01"}=3$, and $K_{"11"}=4$.

3.
   3.1 Calculate the sum P of the occurrence probabilities of all non-impossible cases ($K_j \neq 4$):

$$P = \sum_{j|K_j \neq 4} p_j. \tag{3}$$

   In the above example, P is for case 2a given by $P=0.42+0.12+0.18=0.72$. Note that P equals 1 (and, thus, is irrelevant) if all signals are consistent (case 1a above).

   3.2 Calculate the normalised occurrence probability p_j^* of each case j as

$$p_j^* = p_j/P. \tag{4}$$

   Above, we have calculated $p_{"00"}^*=0.18/0.72=0.25$ for case 2a, for example.

4. Finally, we can determine $bel(\mathrm{H}\uparrow)$ and $bel(\mathrm{H}\downarrow)$ (and, thus, also $pl(\mathrm{H}\uparrow)$ and $pl(\mathrm{H}\downarrow)$) by summing exactly the corresponding normalised occurrence probabilities:

$$bel(\mathrm{H}\uparrow) = \sum_{j|K_j=2} p_j^*, \tag{5a}$$

$$bel(\mathrm{H}\downarrow) = \sum_{j|K_j=3} p_j^*, \tag{5b}$$

$$pl(\mathrm{H}\uparrow) = 1 - bel(\mathrm{H}\downarrow), \tag{5c}$$

$$pl(\mathrm{H}\downarrow) = 1 - bel(\mathrm{H}\uparrow). \tag{5d}$$

How to Determine Signal Reliabilities

We have seen now how arbitrarily many trading signals can be combined with each other. While our calculations were based solely on logical reasoning and, thus, objective, our approach still has a weakness in this regard: For the calculation of (1), it is necessary to know the reliability r_i of each signal S_i. The classical evidence theory regards these reliabilities as given, but we do not follow this assumption because nobody is able to say with which probability a trading signal will be reliable. The manual specification of r_i would introduce an additional degree of freedom and, thus, allow arbitrariness. Therefore, we want to find a mechanistic approach for its calculation.

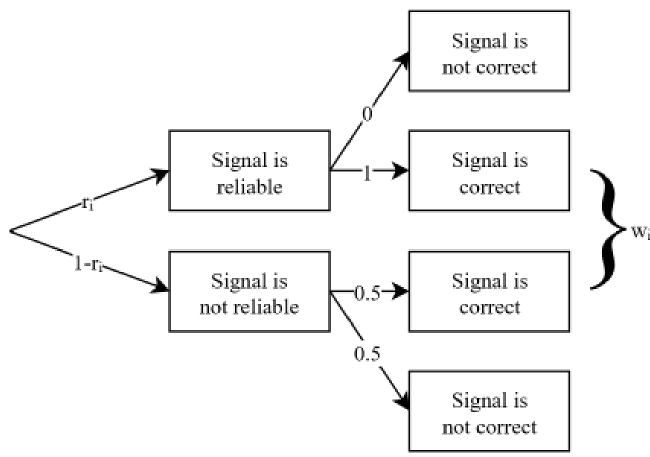
For this purpose, let us consider under which circumstances we would call a signaller such as a guru reliable in practice: this will be the case the more the more often his prognoses prove to be correct. If we know the corresponding share w_i of correct prognoses, we can use this information to calculate an estimate of r_i. This assumption can be regarded as fulfilled in trading because it usually is easy there to evaluate signallers by backtesting. The important thing and a great simplification here is that we can consider each signal separately, as we do not aim here to derive a trading decision. To calculate w_i, one just has to define a certain period of time, say 100 days, and to check how often the signaller has given the correct signal within this period. If this has been the case 60 times, for example, w_i would equal 60% (i.e., $w_i=60/100=0.6$). This value can be updated after each new trading day, whereby w_i gets more and more precise and current. Also, "poor" signallers are automatically attributed less and less weight by this approach, until they are sorted out completely in the end.

It would be a fallacy, however, to simply set $r_i=w_i$, as we already have discussed the main insight of evidence theory that it is not the same whether a signal is reliable (as measured by r_i) or correct (as measured by w_i): Without further information, an unreliable signal is correct in every second case (i.e., with a probability of 50%)! Correspondingly, the relationship between r_i and w_i is more complex; one can interpret it in Bayesian terms and visualise it as shown in Figure 1. By applying the path rule, this relationship can be formalised as $w_i=r_i \bullet 1+(1-r_i)\bullet 0.5=0.5+0.5\bullet r_i$ or

$$r_i = \max(2\bullet w_i - 1; 0). \tag{6}$$ [2]

It can be interpreted intuitively: When a signaller has always given the correct signal ($w_i=1$), it can be taken as perfectly reliable ($r_i=2\bullet 1-1=1$) for the moment. When it has been correct only in every second case ($w_i=0.5$), it is perfectly unreliable ($r_i=2\bullet 0.5-1=0$), as it only "guesses"—it is not better than tossing a coin. When it has been correct even less often ($w_i<0.5$), it is even worse than guessing and again has to be taken as perfectly unreliable (negative values of r_i are not feasible).[3]

Figure 1. Relationship between r_i and w_i interpreted in Bayesian terms



Risk Attitudes and Trading Rule

Being able now to determine the signal reliabilities endogenously, our approach is completely objective. However, traders need to be given the possibility to express their risk attitude, as even when having the same set of information, not all of them will *want* to make the same trading decisions. This subjective component can be taken into account when deriving a trading rule from the calculated belief and plausibility values. The general rule is: A trader should buy when he

- is sufficiently certain that the price will increase, that is $bel(\mathrm{H}\uparrow)>\alpha$.
- has no sufficient reason to assume that the price will decrease, that is $bel(\mathrm{H}\downarrow)<\beta$; in other words, a price increase has to be sufficiently plausible, that is $pl(\mathrm{H}\uparrow)>1-\beta$.

α and β with $\alpha,\beta \in (0;1)$ are the parameters that represent the trader's risk attitude, as they specify what "sufficiently" means to him: The more risk-averse he is, the greater he should choose α and the smaller he should choose β. This should lead to less trades (as the conditions are met less often), while the trades that are done should, in tendency, be more profitable. [4]

The same conditions apply to selling; H↑ has just to be replaced by H↓ for this case. Also, α and β may be chosen differently here, as many studies (the most famous one arguably is the study by Kahneman & Tversky 1979) imply that traders have different risk attitudes for selling than for buying.

Application to Social Trading

Objective

As mentioned earlier, the method developed in this work can be applied to arbitrary trading signals, regardless of whether these are of technical, fundamental, or social origin. The latter group is currently especially interesting, however. This is for one thing because social trading currently is popular due to various platforms such as ayondo or eToro that have been created in the context of so-called "fintech" startups. For another thing, social signals, which here reflect the decisions of successful traders, are usually based on complex algorithms that take into account a lot of different indicators. Therefore, it stands to reason not to consider only one opinion on a given title but to collect and combine as many signals as possible and to invest only in such titles for which there is a broad consensus among the experts on how the price will develop: If the large majority of successful traders, using different approaches, come to the same conclusion, it seems unlikely that this development is not going to realise. We now will check by our method whether this strategy really works as simple as that.

Approach and Dataset

Unfortunately, the architecture of most social trading platforms is not well-suited for such analyses, as there is no possibility to retrieve signals automatically. At eToro (www.etoro.com), currently the largest platform for copy trading (a special case of social trading in which a trader copies the decisions of other traders he follows), it is at least possible, however, to collect the necessary data manually, although this requires a great effort. We used the following approach for data collection:

1. At first, we selected a large number of traders to "copy" (fictitiously). We were careful to get a good mix of traders who had been very successful so far and rather mediocre ones, as our method should automatically attribute a lower weight to the latter. For each trader, we recorded the key figure "% of successful trades", which roughly reflects w_i.
2. For each title contained in the current portfolio of at least one of the considered traders at a certain cut-off day—independently of its type (e.g., stock, index, forex)—we recorded the traders' current positions (long or short) on it (if they had one). Titles that were contained in exactly one portfolio were excluded because if there is only one signal, nothing can be combined. Also, we excluded a few further titles due to other reasons (e.g., missing data problems). Finally, we excluded traders who only had excluded titles in their portfolio.
3. For each remaining title i, we recorded the average prices $K_{i,t} = \frac{1}{3} \cdot \left(\text{Low}_{i,t} + \text{High}_{i,t} + \text{Close}_{i,t}\right)$ at the cut-off day (t=0) as well as at the next day (t=1) and calculated the return $R_i = \frac{K_{i,1} - K_{i,0}}{K_{i,0}}$.

Table 3 summarises the resulting dataset. As can be seen, there are, on average, 4.54 signals for each title, which now have to be combined. It is striking that there is a high percentage of long positions and that the average return per title is significantly positive (t-test: p<0.001). It is to be assumed that these observations have important causes and consequences, which we will elaborate on below.

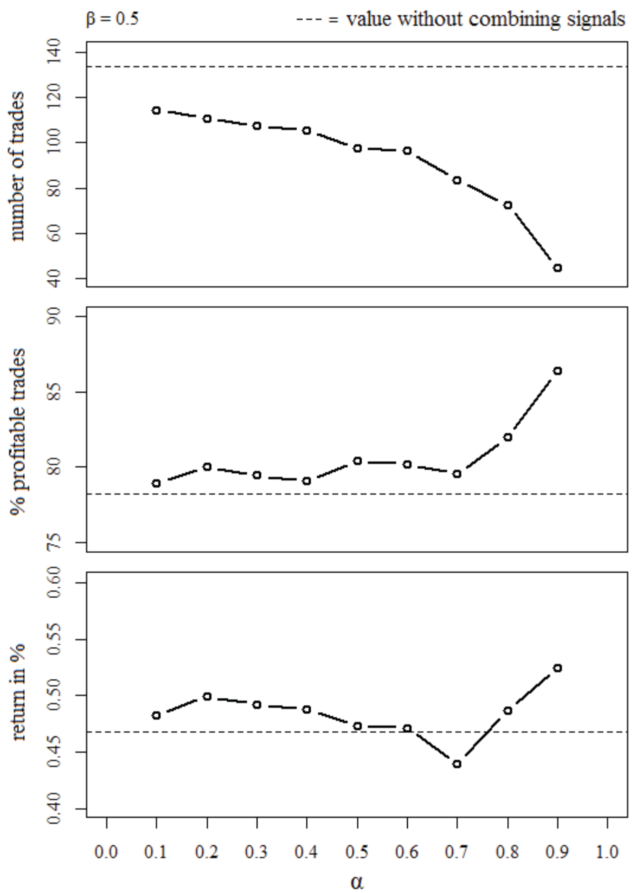
Table 3. Summary of the analysed dataset

Traders		Titles		Signals	
number	120	number	133	number	604
Ø profitable trades (w_i)	68.36%	% price increased after 1 day	78.20%	% long	84.44%
Ø reliability (r_i)	36.73%	Ø return after 1 day (R_i)	+0.47%	Ø no. per title	4.54

Results and Interpretation

The collected signals were combined by our method, which we have implemented in the statistical software R (R Core Team 2016). Figure 2 shows the results for different traders, who are characterised by β=0.5 (other values of β would lead to very similar results in our case) but variable values of α, with regard to three key figures: the number of trades (due to reasons that will become clearer later, we consider only long positions), the share of them that are profitable, and the average daily return.

Figure 2. Results of key figures for different traders



Three results are striking:

First, the number of trades, as expected, decreases with increasing values of α (that is, for more risk-averse traders). It changes only slightly between two subsequent values of α, however, so that small deteriorations of the share of profitable trades or the average return should not be over-interpreted, as they likely occur randomly (e.g., because a very profitable but also very risky trade is not done).

Second, one can see that the share of profitable trades is for all values of α greater than the share of analysed titles for which the price has increased from the cutoff day to the next day (see Table 3). This confirms that the signals given by the considered experts (or rather their combinations) are valuable to a trader. The abovementioned strategy, therefore, seems indeed to be valid.

Third, however, except for the very risk-averse choice of $\alpha \geq 0.8$, it does not seem as if the share of profitable trades and the corresponding average return would increase monotonously with increasing values of α. This is surprising, as we had expected that when more (or more reliable) traders believe in an increase of prices, this is more likely to happen in fact. Several causes may be responsible for this not being the case, but the most plausible one seems to be following: As can be seen from Table 3, more than four of five of the considered signals reflect long positions. It is unlikely that this indeed is because most traders just "by chance" believed in an increase of prices at the cut-off day. Rather, it is to be assumed that many traders always open only long positions. This means that they will not open short positions even if they are convinced that the price will decrease. The data, thus, are biased in this sense, as they give a too optimistic view on the market. This is also reflected by the average return across all considered titles being positive: As traders who only open long positions have invested in exactly these titles, the latter are preselected. For this reason, the abovementioned strategy can only be applied with care, at least as long as one does not have additional data.

Conclusion

Using the method developed in this work, it is possible from now on to objectively combine various trading signals (technical, fundamental, or social ones) with each other. The result of this combination are two figures, $bel(H\uparrow)$ and $pl(H\uparrow)$, which contain the complete information the trader has collected as well as the reliabilities of the corresponding signals. On this basis, he can trade in accordance with his personal risk attitude. Furthermore, it has been shown how the signals' reliabilities can be calculated automatically and, thus, objectively. This would imply that traders now no longer need to decide *which* signals they want to consider at all, as each reliable signal contains information, and each unreliable signal will be attributed less and less weight over time until it is sorted out completely. We have found by applying our method to data collected from a copy trading platform, however, that one in practice has to be careful that the considered signals are not preselected, as the results may be biased otherwise (in our case, they gave a too optimistic view on the market).

Our method can be extended by future research with regard to many aspects. For example, we have restricted our analysis to binary (and, thus, discrete) signals (to buy or not to buy/sell), as this is the type common in social trading. Other signallers such as technical indicators, however, can also give continuous signals. These, of course, can always be discretised, but evidence theory, on which this work is based, can also be extended in such a way that it can make use of continuous signals directly; such extensions make the calculations much more complex, however (see, e.g., Strat 1984 for a start).

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Notes

[1] The alternative that the price does not change could equivalently be subsumed under H↑. It is not of relevance for the following calculations.

[2] The formalisation of the relationship between r_i and w_i in its presented form is simplified because it implicitly mixes up relative frequencies and probabilities. A mathematically rigorous derivation through the maximum likelihood approach would, however, lead to the same result (we omit a proof for brevity). It would also make clearer where the maximum in (6) comes from.

[3] In this case, one should consider reversing the signal, however.

[4] An interesting special case is the choice of $\alpha = bel(H\downarrow)$ and $\beta = bel(H\uparrow)$, which means that a trader buys a title if he believes *rather* in an increase than in a decrease of the price.

Achieve Your Goals More Often

A Case for Active Allocation

By Franklin J. Parker, 2017 NAAIM Wagner Award Winner

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Abstract

We propose a dynamic portfolio optimization procedure that uses markets to predict asset returns as well as risks. Differing from other approaches to outperformance, we couch this approach firmly in the concept of efficient markets, in effect using the efficiency of markets to outperform alternate buy-and-hold strategies. We also incorporate goals-based portfolio theory in an effort to create a strategy that can be used to help investors achieve their goals more often, as this is why most investors interact with public markets in the first place. To build the optimization strategy, we use option market implied volatility to forecast the standard deviation of an asset in the coming month. To forecast returns in the coming month, we utilize the US Treasury yield curve spread (10-Year minus 3-month) as a probability indicator of coming recessions, and then use the probability-weighted sum of returns as the expected portfolio return in the coming month. This information is then used in place of historical return and variance expectations in the optimization model, and the asset allocation is re-optimized (and thus updated) each month. We tested 108 months (9 years), spanning the years 2007 through 2015.

When compared against a historically mean-variance-optimized, passively allocated portfolio, the active allocation approach presented and tested here delivers significant alpha, generally lower beta, and considerably higher probabilities of goal achievement. We find that the monthly increase in return over the passive portfolio (+10.25 basis points, +52.15 basis points, and +64.05 basis points) generated by this strategy is statistically significant at the 5% significance level, though in one test we could not reject the null hypothesis at that level of significance. We further find that, when compared to a simple "buy-and-hold the S&P 500" strategy, the active allocation strategy delivers alpha of 9.70, average excess monthly returns of +62 basis points (statistically significant at the 5% level), lower beta (β = 0.57), and considerably better risk/return efficiency (165% higher Sharpe Ratio). These results are robust even after accounting for the effects of diversification, which leads us to conclude that the superiority of the approach can be attributed to the information content of market-based forecasts.

When interacting with public markets, most people are doing so to achieve some end-goal. It is difficult to imagine an investor saving and sacrificing, then wading into the tumultuous waters of public markets, all "for the fun of it"! In this context, the debates of traditional portfolio theory seem entirely irrelevant. After all, goals-based investors do not necessarily care what percentage a coin must land on heads in order to feel comfortable with the risk taken—a long-standing debate in modern portfolio theory (see especially Markowitz [2010]). Goals-based investors care about achieving their goals!

Given that the efficient market hypothesis (EMH) is the academic and industry default today, this investigation will work under that assumption, offering theoretical and empirical evidence to show that, even assuming efficient markets, it is still possible to outperform on a risk-adjusted basis (create alpha). This investigation also shows how that outperformance can (and should) be channeled for the benefit of investors with goals to achieve. In short, with the techniques presented here, investors have a higher probability of achieving their goals than they do with passive investing alone.

A Quick Tour: Goals-Based Portfolio Theory

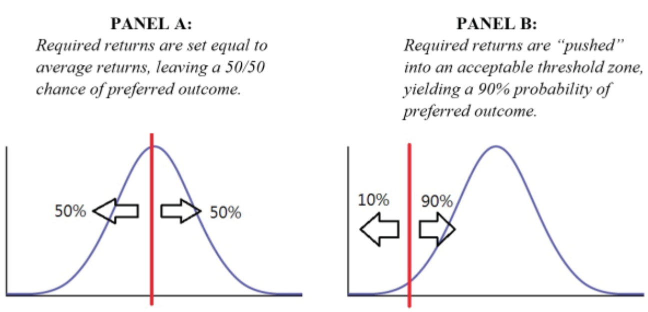
Putting goals at the center of investment theory has only recently been a focus of academic portfolio theory, though practitioners have been using the approach for years. Having begun with the tax-sensitivity studies (institutions such as pension funds and endowments are not subject to taxes—one of their many advantages over individuals) of Jeffrey and Arnott [1993], Brunel [1997] and [1998], goals-based portfolio theory has grown to include the important work of behavioral finance, most importantly the mental-accounting framework of Thaler [1985]; the Prospect Theory of Kahneman and Tversky [1979]; and the Behavioral Portfolio Theory of Shefrin and Statman [2000]. Recently, goals-based theory has caught the attention of investment icons, and a milestone was surely reached with the publication of Das, Markowitz, Scheid and Statman's [2010] paper "Portfolio Optimization with Mental Accounts" which effectively blended the behavioral work done by Shefrin and Statman with the mean-variance efficiency work done by Markowitz. Their work offers two very important insights.

First, rather than attempting to discern an investor's psychological risk tolerance (which is nigh impossible to pin down—see Pan and Statman [2012]), they proposed asking the investor a simple question: *what is the maximum probability of failing to achieve this goal that you are willing to accept?* The practitioner converts this expressed threshold into a risk-aversion coefficient, then proceeds to optimize the portfolio as usual. This at least acknowledges how goal-based investors perceive risk, and allows them to communicate to the practitioner in that language. Brunel [2015, p. 83] takes this a step further and offers a basis in common language, asking the investor to speak of goal priority in terms of "needs, wants, wishes, and dreams." With regard to willingness to accept higher risks of achievement failure, he asks the investor to speak in terms of "nightmares, fears, worries, and concerns."

This can help the practitioner classify which goals are priority (after all, everyone dies with some "dreams" unfulfilled), and which goals are worth reaching for but acceptable if left unfunded.

A second very critical observation of Das, et al. [2010] is that investors must operate with a goals-based discount rate. This is best explained with the help of a picture (see Figure 1). By setting the average expected portfolio return equal to the required return, the practitioner has necessarily given only a 50% probability of goal-achievement (Panel A of Figure 1—the common approach in the industry). This is because, by definition, half the returns fall below the average (which means a failure to achieve a goal). Using a goals-based discount rate moves the distribution of outcomes to the right, pushing the required return into a zone where the majority of outcomes lie (Panel B of Figure 1—the goals-based approach). Notice that this means the portfolio must have a higher expected return than what is required (the red line in Figure 1 is the required return; the peak of the distribution is the expected return). This approach has been shown to give investors a higher probability of achieving their goals.

Figure 1. Two Approaches to Dealing with Required Returns



Another major departure from traditional portfolio theory is a redefinition of risk and reward (discussed extensively by Parker [2016a] and Parker [2016b]). While modern portfolio theory (MPT) equates risk with standard deviation and reward with expected returns, goals-based portfolio theory equates risk with the probability of achieving a goal and reward with excess wealth generated, which is over-and-above the goal. This requires a separate mathematical understanding to properly model—a discussion revisited in later sections.

Theoretical Support: Using Markets to Predict Markets

Market dynamics are understood today primarily through the lens of the efficient market hypothesis (EMH). Central to this idea is that market participants, driven by competition for riskless profit, will actively seek out and react to information as it becomes publicly available. Of course, they will also remember what has already happened—so past data is also taken into account. As affirmation for such an idea, Fama [1970], Fama and French [2010], and others have empirically shown the difficulty of outperforming markets with active management strategies.

We can think of markets much like a dinner party. All of the brightest minds in finance are there—Nobel prize winners, traders who have been at their desk for 40 years, giant hedge fund managers. To trade against such an intelligent and motivated crowd, you would need very strong evidence—maybe even information that is currently unknown. The challenge and cost of finding and using such information very often negates the economic advantage the information provides. But why not *use* this dinner party crowd? If we acknowledge the wisdom of such a crowd, it makes sense to use them to our advantage! We could, for example, ask their collective opinion on various future outcomes. As it turns out, the research literature has already begun to study this idea.

The development of options theory has provided investors with a way to understand the price for things like time (theta), underlying price change (delta), and risk (implied volatility), and the rise of a robust options market has allowed for the price discovery of such items. With a robust and active derivatives market we can, in effect, read the market's expectations for things that we care about, like future volatility. When managing the risk/return tradeoff, information about future risk is half the equation! This assumption, however, requires an efficient derivatives market. Because market efficiency is the default assumption of investors today, we offer only one study of options market efficiency to support this premise: Stein [1989] who finds that, while option markets do tend to slightly overreact short term, they are on the whole informationally efficient. As it happens, the research on the informational content of derivative markets is fairly definitive. Frijns, Tallau and Tourani-Rad [2009] find that implied volatility (IV) does carry significant information about future asset volatility and return, a result echoed by Goyal and Saretto [2008]. In contrast, Bali and Hovakimian [2007] find that IV does not offer much predictive power for future asset returns, but it does offer predictive power for future volatility, a result echoed by Ammann, Skovmand, and Verhofen. Poon and Granger [2003] further find that IV was a better predictor for future volatility than historical volatility in three-quarters of the studies they surveyed.

It would appear that derivative markets *do* offer predictive power, at least for future risk. This idea is furthered by Mostowfi and Stier [2013] along with Miao and Dunis [2005], who both offer a mean-variance optimization and/or risk-control scheme that incorporates the forward-looking information of implied volatility. Both schemes outperformed their benchmarks over the given test period. Given the theoretical and empirical evidence, it seems reasonable to conclude that this information can be used to the benefit of investors. We turn now to information about future returns.

While the literature is not silent on using markets to predict future returns, it is not quite so direct. Leaving aside much of the behavioral work and focusing only on the work that assumes efficient markets, we find that markets are—for the most part—able to foresee coming storms. The challenge, of course, is not in foreseeing a coming storm, but recognizing it *before* prevailing prices account for this expectation. Empirical work done, such as that by Ranson [2016], has shown that certain asset prices tend to be first-movers and strong indicators of pending regime changes—a further indication of the power of market-driven predictions. The yield curve is also a well-known and widely followed indicator; empirically we can see this in Figure 2. Resnick and Shoesmith [2002] have even presented a stand-alone strategy for using a yield curve indicator to enter and exit stocks. Their work has the advantage of out-of-sample robustness, as 2007 through 2009 was not in their sample yet followed the pattern they identified.

The approach presented here takes a simple tack. Without expecting the yield curve to predict asset returns, this approach assumes it is indicative of recessionary/expansionary regimes only. Coupled with an understanding of asset returns within these two regimes, this allows a very simple mechanism for assessing future asset returns.

Figure 2. The Yield Curve as a Predictor of Recessionary Environments, 10-Year US Treasury Minus the 3-Month US T-Bill

(shaded areas indicate recessions, source: Federal Reserve Bank of St. Louis)

Putting It All Together: A Goals-Based, Active Allocation Approach

Armed with firm theoretical footing, we can now piece these disparate theories into one cohesive whole, beginning with the goals-based optimization scheme. In essence, the approach is to understand risk not as standard deviation, but as the probability of failing to achieve a goal. Reward, in turn, is redefined as the return achieved over-and-above the minimum required to fund a goal. We then aim to minimize the probability of goal-failure, and maximize the returns over-and-above the minimum. Mathematically, we understand this as:

$$\min\Phi(r_{req.} \mid R, \sigma) \qquad (1)$$

$$\max(R - r_{req.}) \qquad (2)$$

where $r_{req.}$ is the annual return required to achieve a goal, R is the expected return of the portfolio, σ is the standard deviation of the portfolio, and $\Phi(\cdot)$ is the cumulative distribution function,[1] which measures the percentage of possible returns which fall below $r_{req.}$. The portfolio optimization objective is to adjust the weights of given assets so that equations (1) and (2) are satisfied.

But this is a backward-looking approach, and the goal here is to incorporate forward-looking information. To understand where the theory enumerated above fits, we need to break down the variables. We begin with our understanding of portfolio standard deviation—note that standard deviation is NOT how we define risk in a goals-based setting. We understand σ as:

$$\sigma = \sqrt{\sum\sum w_i w_j \sigma_i \sigma_j \rho_{ij}} \qquad (3)$$

where w_i is the proposed weight of asset i, w_j is the proposed weight of asset j, σ_i is the standard deviation of asset i, σ_j is the standard deviation of asset j, and ρ_{ij} is the historical correlation of asset i to asset j. By replacing historical standard deviation figures with implied volatility (which is forward looking), we can account for the market's expectation of future standard deviation. So, replacing σ_i with V_i and σ_j with V_j where V is the implied volatility of a given asset, then:

$$\sigma = \sqrt{\sum\sum w_i w_j V_i V_j \rho_{ij}} \qquad (4)$$

is the standard deviation formula that should be used in equation (1). Recall, the information we propose incorporating is information about future volatility, which has been highlighted in this equation.

To incorporate information about future return, we turn to the findings of Resnick and Shoesmith [2002]. They show that the US Treasury yield curve from 10 months ago has predictive qualities for economic environments; specifically, we use the 10-Year US Treasury minus the 3-Month US T-Bill. Figure 3 lays out their recession probability findings. Notice that as the spread compresses and inverts, recession probabilities increase. Though their study is over a decade old, their data has the advantage of being accurate out-of-sample, and we therefore see no reason to reinvent the wheel. There is one exception—we looked in the historical data for recessionary *market* environments rather than strictly *economic* environments.

Figure 3. Bear Market Probabilities Based on the Yield Curve from 10 Months Ago

Probability	Percentage Points of Spread
0%	> 2.54
10%	2.54 to 1.38
20%	1.38 to 0.55
30%	0.55 to (0.17)
40%	(0.17) to (0.83)
50%	(0.83) to (1.5)
60%	(1.5) to (2.21)
70%	(2.21) to (3.05)
80%	< (3.05)

We then used these recessionary market environments to develop an understanding of how various asset classes behave during those environments. Figure 4 displays the historical returns of the asset classes we tested in the two market environments. We incorporated T-Bills in our tests; however, to compensate for the bias of the historical data and to prevent time-travel bias, we used the previous calendar year T-Bill yield as the yield expectation for the year in which a test occurs.

Figure 4. Asset Returns in Recessionary and Non-Recessionary Environments, 1968–2006

	S&P 500	Gold	20-Yr US Treasuries
Non-Recessionary	16.24%	8.04%	(0.05%)
Recessionary	(11.60%)	18.21%	2.48%

To account the recession/non-recession probability implied by the market, we must re-think the portfolio return definition somewhat. Equation (5) shows the result of this re-thinking:

$$R=(1-\mathbf{P})\cdot\sum w_i m_i + \mathbf{P}\cdot\sum w_i n_i \quad (5)$$

where P is the yield-curve implied probability of a recessionary environment, w_i is the proposed weight of a given asset, m_i is the return of a given asset in a non-recessionary environment, and n_i is the return of a given asset in a recessionary environment. In short, the portfolio expected return can be thought of as the probability-adjusted sum of returns. As before, we have highlighted the information carrier set by the market. As an example: suppose the yield spread from 10 months ago was 0.25 percentage points. Using Figure 3, we could infer the probability for a recessionary environment was 30%. Coupled with the return expectations of Figure 4 and equation (5), an equal-weighted portfolio (25% weight to each asset) would have an annualized return expectation of 6.92%.

Equation (5) and equation (4) can now be substituted into equations (1) and (2). For ease of reference, we have done this with equations (6) and (7):

$$\min \Phi\left(r_{req.} \mid (1-P)\cdot\sum w_i m_i + P \cdot \sum w_i n_i \ , \sqrt{\sum\sum w_i w_j V_i V_j \rho_{ij}} \right) \quad (6)$$

$$\max \ \left(\left[(1-P)\cdot\sum w_i m_i + P \cdot \sum w_i n_i\right] - r_{req.} \right) \quad (7)$$

$$\text{subject to:} \quad \sum w_i = 1 \text{ and } 0 \le w_i \le 1 \quad (8)$$

Notice that equation (8) is the standard no-short-sale and no-leverage constraints. Because this investigation is aimed at goals-based investors (for whom short sales and leverage are usually excluded), we did not test the removal of these constraints.

We should, perhaps, pause here to recap how this optimization scheme is constructed.

1. **First, a goals-based understanding of risk** (and thus optimization) **is used.** This approach advocates the use of phi (Φ), which measures the probability of goal-failure, as the primary metric for risk.
2. **Second, we have incorporated implied volatility as the market's future expectation for volatility** (standard deviation). This allows the optimization scheme to account for the forward-looking nature of the market.
3. **Third, we use the yield curve coupled with historical asset returns in recessionary and non-recessionary environments to generate expectations for future asset returns.** The study on which this thesis is based infers that the information content of the yield curve is lagged by 10 months. Therefore, we use yield curve information from 10 months ago as our indicator.
4. **Fourth, we blend all of this into an optimization scheme that is updated/rebalanced monthly.** The inputs and subsequent asset allocation are updated monthly using the market's expectation for future risk and return, in context of the investor's goal.

Talk (and Theory) Is Cheap: Does It Work?

For our proof-of-concept test, our investible universe was four assets: S&P 500, Gold, 20-Year US Treasuries, and 3-Month T-Bills. Serving as benchmarks (control tests), we used a passive portfolio optimized using historical data. Variance, return, and correlation data were updated annually, and we conducted a monthly walk-forward test beginning January 2007 and ending December 2015 (9 calendar years). Our test portfolio was optimized monthly using the scheme presented in the previous section. Implied volatility and recession probabilities were updated monthly, whereas historical correlations were updated annually. Again, a monthly walk-forward test was performed. In an attempt to rule out a possible statistical anomaly, we tested three different portfolios over the same time period: a 4% required return, a 6% required return, and an 8% required return. To determine which approach yields better goal-achievement probability, we further tested each portfolio over various rolling time periods: 36-month, 60-month, and 84-month.[2] This yielded a total of nine time-series tests.

For each actively allocated portfolio, the procedure was:

1. Input the four-week average implied volatility figure, calculated on the last trading day of the month, into the covariance table.
2. Input the yield-curve information from 10 months ago, which is translated into a recessionary probability.
3. Asset correlations are updated at the end of each year tested.
4. Optimize allocation monthly to minimize phi (Φ).
5. Updated allocations are then used to calculate a growth rate for the given month.
6. Repeat procedure for the 108 months tested.

The procedure for the passive portfolio tests was similar, but historical data was used rather than the forward-looking data we propose:

1. Build covariance tables using historical monthly correlations and standard deviations.
2. Optimize allocation at the beginning of the year to minimize phi (Φ).
3. Rebalance the portfolio to the target allocation (which was determined in step 2) every month.
4. Update covariance tables at the end of each year.
5. Re-optimize using updated historical data, and repeat procedure through the coming year.

Ultimately, the figure by which we must judge the approach is the actual probability of achieving a goal. We have certainly included other metrics, such as beta, alpha[3] and Sharpe ratios, but goal-based investors ultimately care about achieving their goals. Goal achievement is the *only* metric that matters to them; it should, therefore, be the only metric that matters to us as practitioners. Nonetheless, we also present more traditional metrics in an effort to help judge the relative benefit of this approach.

Figure 5. Test Results

	2007 - 2015 Monthly Walk-Forward Tests	PASSIVE Goal Acheivement Frequency	PASSIVE Average Annualized Return	PASSIVE Annualized Standard Deviation	PASSIVE Sharpe Ratio	ACTIVE Average Change in Monthly Return (basis points)	ACTIVE Average Annualized Return	ACTIVE Annualized Standard Deviation	ACTIVE Sharpe Ratio	ACTIVE Alpha over Passive	ACTIVE Beta over Passive	ACTIVE Change in Efficiency	ACTIVE Goal Acheivement Frequency	ACTIVE Change in Goal Acheivement Freq. (percentage points)
4% Rreq.	36 Month	0%											30%	30.14
	60 Month	0%	1.13%	2.76%	0.32	10.25	2.36%	4.76%	0.45	0.83	1.45	38%	27%	26.53
	84 Month	0%											0%	0.00
6% Rreq.	36 Month	64%											100%	36.00
	60 Month	61%	5.10%	13.07%	0.37	52.15	11.35%	14.15%	0.79	6.77	0.89	111%	100%	39.00
	84 Month	28%											100%	72.00
8% Rreq.	36 Month	59%											97%	38.00
	60 Month	53%	5.21%	13.38%	0.37	64.05	12.90%	14.80%	0.85	8.52	0.83	130%	98%	45.00
	84 Month	16%											100%	84.00

A look through Figure 5 illustrates the success of this approach—at least over the most recent market cycle. As Parker [2014] shows, drawdowns can wreak havoc on impending goals. We have therefore decided to begin the test in 2007—at the most inopportune time for a goals-based investor.

Nonetheless, by all metrics measured, the incorporation of the market's expectations increases returns and/or decreases risks. In all three return requirements, the actively allocated portfolio generated alpha—in two of three cases, alpha was in excess of 6.0. Furthermore, the actively allocated portfolios greatly increased portfolio efficiency (as measured by Sharpe ratios)—in two of three cases, the active portfolio *more than doubled* the efficiency of the passive portfolio.

Judging the procedures by which investors judge our procedures, we find that the active portfolios increase an investor's ability to achieve goals in eight out of nine tests, with one test resulting in no change. In all, the average increase in goal achievement probability is 41 percentage points. That is the difference between achieving goals 31% of the time and 72% of the time—a *very* significant difference for investors!

We also conducted hypothesis tests concerning the difference of average monthly returns. For the 4%, 6%, and 8% $r_{req.}$ portfolios, we wanted to determine whether the increase in monthly returns over the passive portfolio was statistically significant. Our null hypothesis was that the mean difference of monthly returns was less than or equal to zero (H_0: $\mu_d \leq 0$ versus H_a: $\mu_d > 0$), which, if rejected, would indicate that the active portfolio is statistically superior in average monthly return to the passive portfolio. For the 8% and 6% $r_{req.}$ portfolios, we were able to reject the null in favor of the alternative at the 5% level of significance. However, for the 4% $r_{req.}$ portfolio, we were unable to reject the null at the 5% level of significance. Therefore, we are led to conclude that the procedure does not increase monthly returns in a statistically significant way for the 4% $r_{req.}$ portfolio, but the average increase in monthly return *is* statistically significant for the 6% and 8% $r_{req.}$ portfolios.

Due to the nature of the optimization scheme, the 8% $r_{req.}$ is comparable to the S&P 500 in terms of expected return and volatility. As a further robustness test, we conducted a direct comparison of the active portfolio to the S&P 500. In an effort to factor out the effects of diversification through the 2007–2009 downturn, we also present the passive portfolio. Figure 6 illustrates the result of this comparison.

Figure 6. Strategy Comparison to the S&P 500

	S&P 500	8% Active	8% Passive
Annualized Return	5.39%	12.90%	5.21%
Standard Deviation	16.05%	14.80%	13.38%
Sharpe Ratio	0.32	0.85	0.37
Treynor Ratio	0.05	0.22	0.06
Beta to S&P 500	1.00	0.57	0.77
Alpha Over S&P 500	-	9.70	1.01
Max Monthly Drawdown	(18.05%)	(17.64%)	(17.95%)

A look through Figure 6 shows that this approach is indeed superior to a buy-and-hold of the S&P 500. Our test results indicate that an investor can expect an extra 62 basis points *per month* of return from this strategy over the S&P 500. And, because the Sharpe ratio of the active portfolio is considerably higher than the S&P 500, the investor is gaining this return with proportionally less risk. Furthermore, when benchmarked to the S&P 500, this strategy generated alpha of 9.70!

We conducted another hypothesis test to determine if this monthly excess return over the S&P 500 was statistically significant. Again, our null hypothesis was that the monthly average difference in return was less than or equal to 0, while our alternative hypothesis was that the return difference was greater than 0 (H_0: $\mu_d \leq 0$ versus H_a: $\mu_d > 0$). We were able to reject the null in favor of the alternative at the 5% significance level. This would indicate that the excess return over the S&P 500 is statistically significant.

Of course, some of these benefits may simply be garnered from the effects of diversification. The passive portfolio, however, should account for those benefits. Recall, we found that the excess returns of the active portfolio over the passive portfolio were statistically significant. Therefore, it is reasonable to conclude that the active allocation strategy is superior to a buy-and-hold strategy on the S&P 500, and that this effect must be attributable to the incorporation of market-driven expectation information.

Goals-based investing is exceptionally path-dependent. So, though it is only one path, we have further illustrated the growth of $1 from January 2007 through December 2015 for each portfolio tested (Figure 7). In all cases, the ending value of the actively allocated portfolio is significantly higher than the passively allocated portfolio. In fact, the ending value of the 4% $r_{req.}$ actively allocated portfolio is $1.22 versus $1.10 (11% higher, Panel A); the ending value of the 6% $r_{req.}$ actively allocated portfolio is $2.53 versus $1.46 (73% higher, Panel B); and the ending value of the 8% $r_{req.}$ actively allocated portfolio is $2.88 versus $1.47 (95% higher, Panel C).

Also of note is the result of the S&P 500 buy-and-hold approach versus the actively allocated 8% $r_{req.}$ strategy (Panel D of Figure 7). $1 invested in the S&P 500 in January 2007 grew to $1.44 by the end of 2015. In contrast, $1 invested in the active allocation strategy grew to $2.88 over the same period. That is a difference of 100%. Put differently, an investor would have *double* the amount of wealth if they had utilized this strategy over a simple buy-and-hold of the S&P 500 during the period of 2007–2015.

It does seem reasonable to conclude that the procedure proposed here can legitimately be expected to generate higher levels of wealth over passive strategies.

Figure 7. Growth of $1 for Various Portfolios: Active vs. Passive, 2007 Through 2015

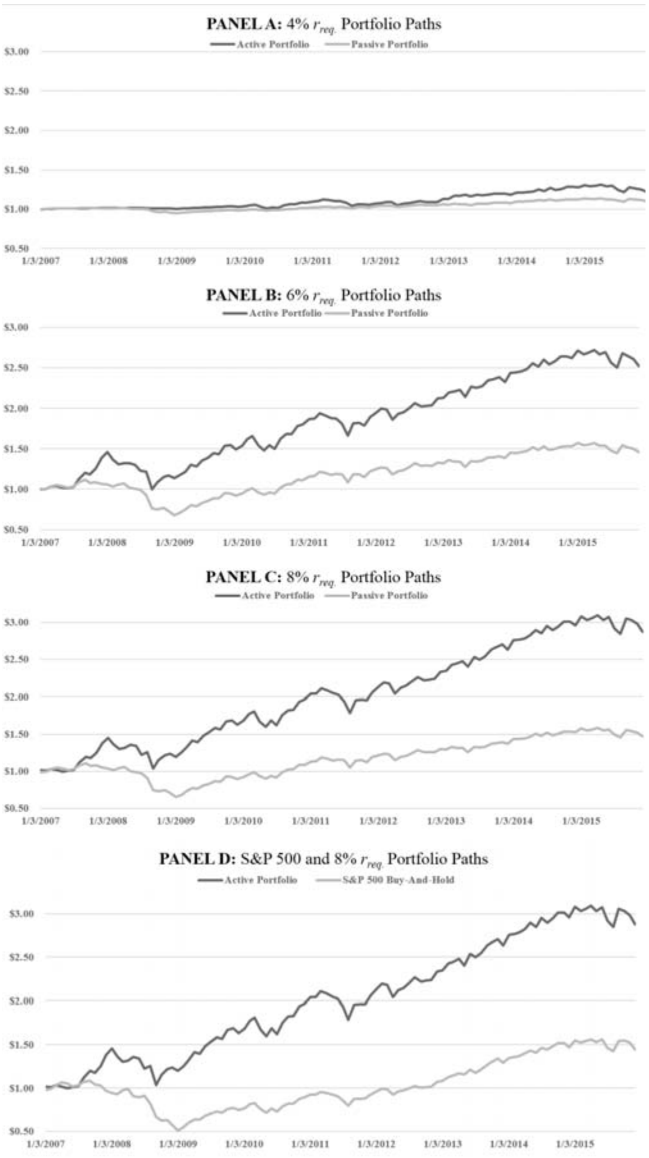
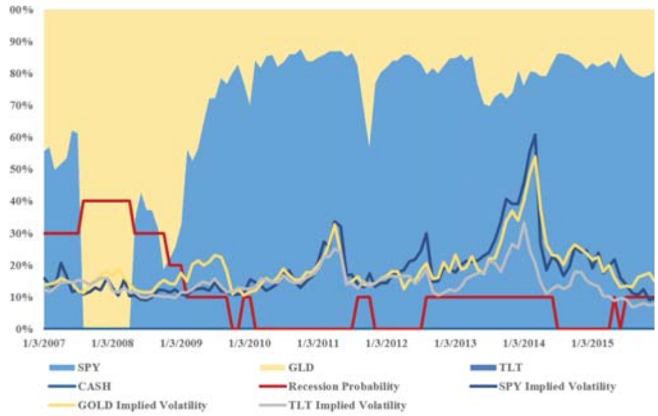


Figure 8. Dynamic Monthly Allocations Example, 6% $r_{req.}$ Portfolio — Monthly Asset Allocation (area chart) With Implied Volatility and Recessionary Environment Probability Overlays (line charts)



Conclusion

The difficulty in measuring the value of active investing is well known in the industry. Furthermore, many researchers have concluded that active management cannot be reasonably expected to deliver consistent alpha, pointing to market efficiency (and empirical evidence) as the primary rationale for that premise. We turn that argument around. If markets are indeed efficient (or at least mostly so), then the risk and return projections of markets should incorporate all publicly available information and should be a fair and reasonable estimate of future outcomes. We can, therefore, use market expectations as a basis for managing a risk/reward tradeoff, and thus generate alpha.

Our statistical tests confirm that we have reasonable basis to accept that the average monthly returns of the active strategy presented here are superior to those of the passive strategy, and superior to a simple "buy-and-hold the S&P 500" strategy. Furthermore, we have shown how taking an active approach can give investors higher probabilities of achieving their goals. At the end of the day, this is the metric we care about because this is the metric investors care about.

Yet we cannot discount the importance of the theoretical support for this approach. After all, without a firm understanding of why something works, we cannot be certain that it will continue to work into the future. Furthermore, without a firm understanding of the "whys," we cannot know which marketplace changes might cause the strategy to stop working. Both of these could leave us vulnerable and potentially chasing a strategy that has ceased to work because of some third thing to which we are blind. Keeping a vigilant eye on the relative efficiency of markets and being wary of overreactions would be key to the continued success of this strategy (see Thaler [2015] and Barberis and Thaler [2003]).

Due to the difficulty of collecting historical implied volatility data, our tests were limited to the 2007 to 2015 period. However, because that period incorporates a significant market downswing as well as subsequent rally, we would expect these results to be robust across market cycles.

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Notes

[1] To clarify the notation of the cumulative distribution function that we use here:

$$\Phi(x \mid \mu, \sigma) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} \frac{e}{\sigma}^{-(x-\mu)^2 / 2\sigma^2}$$

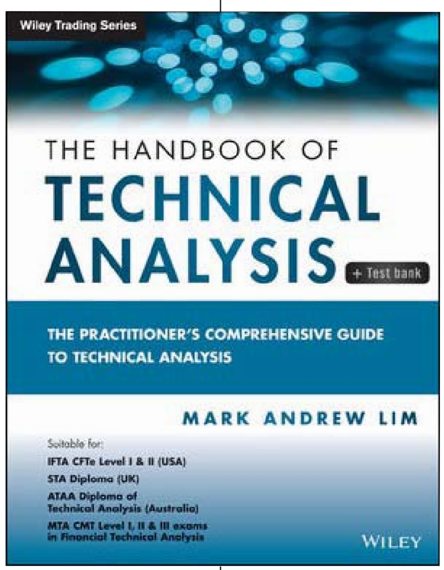
[2] For clarification: one 36-month rolling time period would be 01/01/2007 to 12/31/2009, another 36-month rolling time period would be 02/01/2007 to 01/31/2009, etc.

[3] For the purposes of this discussion we use Jensen's [1967] alpha: $\alpha = r_i - (r_f + \beta_{i,m} (r_m - r_f))$ where r_i is the return of the investment portfolio, r_f is the risk-free rate (we used the average risk-free rate in our comparisons), $\beta_{i,m}$ is the investment portfolio's beta relative to the market (or benchmark portfolio), and r_m is the return of the market (or benchmark portfolio). For ease of presentation, we have multiplied alpha by 100.

The Handbook of Technical Analysis—by Mark Andrew Lim

Reviewed by Regina Meani, CFTe

After spending some time working with the late, great John Brooks on the Body of Knowledge for IFTA, I was intrigued by the title *The Handbook of Technical Analysis* and its cover comments indicating that it was "The Practitioner's Comprehensive Guide to Technical Analysis," and more importantly, that it was suitable for both the IFTA CMT Association (formerly the Market Technicians Association) courses. What I find significant here is the word "suitable" and that the book is not on the "recommended" reading list for potential students of technical analysis and those wishing to sit for the exams for the international bodies. While this is by no way a criticism of this most comprehensive tome, it is a word of caution. As part of the Kaplan task force (the Australian exam body), I know that some of the exam questions require that the answers stick strictly to the syllabus. I stress this point, as I have noted in my reading of the book, that Mark Lim does not always adhere to the traditional concepts and methods of technical analysis. I applaud those who offer different and individual interpretations, but for the uninitiated and those wishing to sit for the exams, I suggest that they primarily rely on the official reading lists provided and use The Handbook as an additional guide.



This almost 1,000-page volume at first appears a bit daunting, especially I imagine to the beginner, and it was apparent that to do Mark Lim's book justice would take far more space than this review would allow. So rather than review the book in its entirety, I broke it down into sections or chapters. I suggest that this approach may ease the reader's navigation by perhaps starting with those areas of technical analysis that interest you most. Read the introduction, as it will give you a guide to prioritising the chapters.

I found Chapter 13 on chart pattern analysis to be beneficial, with some of the author's ideas perhaps lacking in some of the older, more traditional books, with its suggestions on how a trader should react and use the patterns to their advantage. This may be useful for the student, and the section was comprehensive and detailed with clear illustrations. Another part of the chapter that caught my attention was Apex Reaction Analysis, which is a useful tool.

In Chapter 14, Japanese Candlestick Analysis, Lim incudes section three on integrating Candlestick patterns and provides some useful insight into overlaying chart patterns, cycles, support and resistance, oscillators, and Ichimoku and Fibonacci, as well as volume and moving averages. The section is not very in-depth, however, but enough to inspire further investigation.

Chapter 24 deals with the concept of relative strength and its importance in gauging the differences between and observing the relationships of stocks within or between sectors or entire markets. It is a well-used, and deservedly so, instrument of technical analysis. Again Lim's attention to detail and examples are extensive, clear and precise. He explains how these studies add a further dimension to how markets and stocks relate to each other and interact. It helps the trader or investor identify areas of weakness or strength, thereby enhancing their ability to time their market participation.

Moving on to Chapter 25, Lim delves into the realm of Investor Psychology. He acquaints us with the general behavioural aspects of our expectations, which is a market driver, and the emotions tied to these expectations and how these manifest into chart patterns and trends, which become self-fulfilling as they install a mindset. *Once a trader is influenced by this mental frame of a trend in effect, which is anchored by elements associated with the representation, all subsequent decisions and actions tend to be trend promoting.* [1]

Interruptions to the trend are seen as the interplay of greed, hope and fear in a wide-ranging and volatile focus, which very often evolves into a consolidation. The natural progression from this is the climax of emotions that occurs at market tops and bottoms and can characterised by high-volume participation and traders being affected by cognitive dissonance—the *discomfort or anxiety when being confronted with contradictory evidence.* [2]

The above is a mere slice taken from the 29 chapters that take the reader from the origins of the Dow Theory, the mechanics of charting, identifying trends, and using moving averages and indicators through Elliott, Gann and Fibonacci principles and into risk profiling, money management and trading systems. It is indeed a "Practitioner's Comprehensive Guide".

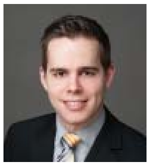
Notes

[1] M.A. Lim, The Handbook of Technical Analysis, John Wiley & Sons, Singapore, 2016, p. 819

[2] ibid, p. 814

Author Profiles

René Brenner



René Brenner studied mathematics and physics at the RWTH Aachen University and is currently working on his Ph.D. in mathematics at the Institute of Mathematics at the RWTH.

Konstantin Dimov, MBA, MFTA, CFTe

Konstantin Dimov has been a technical analysis practitioner for nearly a decade. In his MFTA research paper "K-Divergence", he presents a theory on one of the most conspicuous price phenomena—"gaps". Konstantin's theory diverges from traditional theories, as it shifts the focus of analysis from the gap itself to the range of prices preceding it. Furthermore, he proposes an alternative gap classification system that is strictly based on the price movement prior to the gap occurring. In his work, he systematically tests the trading strategies originating from the K-divergence theory as well as provides a concrete framework on how technicians should apply the theory when analyzing securities on an individual basis. In 2012, Konstantin obtained a bachelor of business administration degree, double specializing in finance and economics, from the Schulich School of Business in Toronto, Canada. During the following three years, he consecutively passed all exams for the Chartered Market Technician (CMT) and Chartered Financial Analyst (CFA) designations while also becoming a Certified Financial Technician. Most recently, he returned to Schulich and completed an MBA with a concentration in Investment Management. Konstantin is a member of the Canadian Society of Technical Analysts.

Akram El Sherbini

Akram El Sherbini holds a B.Sc. in physics from the American University in Cairo. He is currently studying for an MBA at Heriot-Watt University. Akram has been involved in financial markets since 2007. Prior to freelancing, he was a technical analyst at Synergy Capital Markets and a 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. Akram is also a member in the Egyptian Society of Technical Analysts (ESTA).

Mohamed Fawzy, MFTA, CFTe

Mohamed Fawzy is currently working as portfolio and fund manager in the Asset Management Department at one of the biggest banks in the UAE, Union National Bank. Mohamed possesses strong expertise in equity asset management, including portfolio management, trading, security analysis, client relationship management, finance, economics, and investment consulting. He has been presented with the Best Asset Manager award in the UAE at the Middle East Summit and Awards 2014 and 2015. Mohamed's academic credentials include a master's degree in financial management and a bachelor's degree in commerce, finance, and accounting (dual degree specialization). In his MFTA research paper, "M-Oscillator", he introduced an oscillator to fix the problems associated with the traditional momentum oscillator, such as absence of boundaries (overbought and oversold) and disproportionate moves in the momentum line vis a vis prices. The indicator also works as a trend identifier.

Detlev Matthes

Detlev Matthes was born in Dresden, Germany. He studied technical computer science (FH) and is an architect and software developer in the telecommunications industry. In his free time, he passionately pursues the design and development of trading systems. He is the creator of the simulations and chart software "PipMaster".

Regina Meani, CFTe

Regina Meani 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, carrying 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.

Franklin J. Parker

Franklin J. Parker is the chief investment officer with Bright Wealth Management in Lewisville, Texas. In this role, he is responsible for all aspects of research, portfolio management, economic updates and capital market assumptions for the firm. As a practitioner-researcher, he is the author of numerous peer-reviewed papers, trade publications, and he is the recent recipient of the National Association of Active Investment Managers 2017 Founder's Award. Franklin attended the University of North Texas where he graduated cum laude, was a Minnie Stevens Piper Scholar and a Board of Regents scholar. Though raised on the family cattle ranch in Central Texas, Franklin, his wife, and children now call North Dallas their home.

Alexander Spreer, MFTA, CIIA, CEFA, CFTe

Alexander Spreer is the regional group manager of the VTAD in Munich and works for an independent asset manager. He is specialized in quantitative technical analysis of equity indices, quantitative stock picking and investment process development. He also uses quantitative methods to analyze economic data. In addition, he works with a small team of people to develop a backtesting and automated trading proprietary software, with the aim of running their own investment strategy based on diversified strategies and new methods of risk and money management.

Tomoyo Suzuki, Ph.D., CMTA, MFTA, CFTe

Dr. Tomoya Suzuki received his B.S., M.S., and Ph.D. degrees in physics from the Tokyo University of Science in 2000, 2002, and 2005, respectively. Then, he joined Tokyo Denki University as an assistant in 2005 to teach electric circuits. From 2006 to 2009, he was a lecturer of Doshisha University, teaching computer languages and computer engineering. Since 2009, Dr. Suzuki has been an associate professor and then a professor of Ibaraki University, teaching mathematics, statistics, and computer science. His research interest is the physics of complex systems, especially financial markets, and his research methods are time series analysis, prediction, machine learning, and data mining with computers. In particular, his recent research is involving the integration of technical analysis, physics, and computer science. From this viewpoint, his MFTA research paper has reported that nonlinear prediction models based on neural networks have a high potential for developing new technical analysis methods. Moreover, he also has a great interest in evidence-based technical analysis and has been giving seminars for NTAA members to emphasize it.

Dr. Patrick Winter

Dr. Patrick Winter lives in Germany. He has earned two B. Sc. 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 and regularly applies it to trading. For these articles, he won awards of the VTAD (Association of Technical Analysts in Germany) three times in a row. He usually does not trade himself, however. This is because he believes that it is even more efficient to create value than to trade it, especially as people then have an incentive to work with rather than against each other. To realize this, Patrick Winter currently prepares the formation of a startup.

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