…the true speculator is one who observes the future and acts before it occurs. Like a surgeon he must be able to search through a mass of complex and contradictory details to the significant facts. Then still like the surgeon, he must be able to operate coldly, clearly, and skillfully on the basis of the facts before him.

—Bernard Baruch
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IFTA 2012 25th Annual Conference

Singapore

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Dear IFTA Colleagues and Friends:

In the very beginning, Technical Analysts were called “chartists.” They were those who plotted and analysed market price data in order to predict the markets. In the general public perception, this was nothing other than reading tea leaves. Yet it was in this period that many ideas were developed on how to graphically describe price movements, and how to come to conclusions from these graphs. Since then, there has been much development and change, and Technical Analysts borrow from disciplines such as psychology, statistics, computer science, information theory or even physics. Now, in the age of seeming unlimited computer capacity, every tool that helps analysing market data qualifies as technical analysis.

The IFTA Journal depends entirely on the papers and articles that we receive from our IFTA colleagues. To start, we do not have a plan or a theme that we want the journal to follow, but instead allow the flow of submissions to determine the theme. For this year, it turns out that the main theme is volatility. We have included different papers on that subject, from the very basic volatility breakouts to more complex treatments of volatility and correlation relationships. Nevertheless, a very broad range of technical topics are covered, including Gann analysis, heuristic pattern search within the MACD indicator, and a specific method to define moving averages based on modern cycle theory.

The journal mirrors the true spirit of IFTA. It is a forum where market technicians from around the world come together and speak the same language. You will read papers from Australia, Africa, Europe and America. Some of the papers are abridged versions of prize winning papers from local technical societies. To this, a special thank you goes to the German society VTAD which helped to motivate their local prize winners to rewrite their papers for us. The other papers are colleagues’ MFTA papers with two book reviews from our Australian colleagues.

A number of changes occurred within the IFTA Journal this year. Regina Meani (APTA, ATAA, STA), our editor for the last four years, stepped aside. Regina reanimated the journal and it is due to her efforts and energy, we have this internationally published platform where technicians can present their ideas. Thank you very much, Regina.

This year’s journal was produced by a new team. I want to thank Elaine Knuth (SAMT, AAPTA) for copy editing the papers in this journal. Without her help, dedication, technical knowledge and hard work, this journal would definitely not exist.

I would also like to thank Linda Bernetich and Jon Benjamin for their input in publishing the journal and last but not least, Michael Samerski (ATAA, APTA) and Mark Brownlow (ATAA, APTA) for their part in the reading and selecting of the papers.

A lot has happened during the course of the year. Much news turned out to be just volatility, but some rather severe events occurred in Japan this spring. Therefore, I would like to dedicate this journal to our friends of the Nippon Technical Analysts Association (NTAA). Let us remember that the very first Chartists came from Japan where Technical Analysis was born.
Introduction
Moving Average Convergence/Divergence (MACD), constructed by Gerald Appel is a well known and established indicator in technical analysis. There is the MACD indicator and the MACD Histogram indicator. The MACD indicator consists of three exponential moving averages, two of them represent the MACD line, which responds quickly to price changes, while the third line represents the Signal line, which responds slowly to price changes, and is made of the MACD smoothed with another Exponential Moving Average (EMA). In this paper we are concerned with the Histogram form of the MACD indicator, rather than the normal MACD indicator.

John J. Murphy stated the following about the MACD Histogram: “The Histogram consists of vertical bars that show the difference between the two MACD lines.” By subtracting the Signal line from the MACD line, the resulting difference is then plotted in the form of vertical bars above or below a line called Zero Line (Figure 1).

In this paper I will, first, define the Head-and-Shoulders pattern on MACD Histogram as well as the different types and forms of the pattern, which can be recognized on the chart, in addition to showing how to recognize the pattern, while it is still forming on the chart.

Secondly, I will illustrate the trading techniques to trade this pattern and how to benefit from its appearance to detect the market direction and generate profits.

Finally, I will conduct a statistical analysis test for the Head-and-Shoulders pattern on the MACD Histogram indicator to examine the frequency of its appearance, as well as its degree of predictability.

Methodology
This study uses daily data via Reuters© from diversified markets and equities to make statistical analysis on the Head-and-Shoulders MACD Histogram pattern. These markets are:

- Dow Jones industrial average (.DJIA)
- General Electric stock (GE)
- Silver (XAG=)
- British Pound Sterling (GBP=X)

These four instruments cover three major liquid markets: U.S. equities (Dow Jones Industrial Average as a market index and General Electric as an individual stock), commodities (silver) and currencies (British Pound Sterling). These instruments have long history and adequate examinable amount of daily data.

To standardize analysis, daily charts and daily data for each one of the four markets for the period starting January 1983 till December 2009 were used. This period of 27 years is the only period that has reliable available daily data for all the four examined markets.

Before 1983, reliable data for silver, British Pound Sterling and General Electric are missing. Dow Jones data goes back to 1907 and is used used in one example.

Various markets are examined to show that this pattern is applicable in non correlated markets. Additionally, we measured the differences in frequency of appearance of the pattern and differences in profitability.

This study examines the following:

- Number of appearances of the Head-and-Shoulders pattern on the MACD Histogram indicator during the period under examination;
- Success/ Failure rate of the pattern;
- Average Profit/Loss of the pattern;
- Average time duration of the move.
Types of Head-and-Shoulders patterns on the MACD Histogram indicator

The Head-and-Shoulders pattern emphasized here is not the classic and traditional Head-and-Shoulders pattern that appears on the price side of the chart, formed from the price bars or candlestick. Instead the pattern we examine appears on the indicator’s side of the chart and specifically on the MACD Histogram indicator.

The MACD Histogram Head-and-Shoulders pattern is very similar to the price Head-and-Shoulders pattern in appearance, and its definition.

There are two forms of the Head-and-Shoulders pattern, as follows:

A—Normal Head-and-Shoulders:

In this case the pattern appears on the positive side of the MACD Histogram indicator above the Zero line.

We can use Dr. Alexander Elder’s definition of the Price Bars Head-and-Shoulders that states: “The head is a price peak surrounded by two lower peaks, or shoulders.” The same definition can be applied to the pattern on the MACD Histogram indicator, but with substituting the word ‘price’ in the definition with the words ‘MACD Histogram’s Vertical Bars’, so it will read as follows: “The head is a ‘MACD Histogram’s Vertical Bars’ peak surrounded by two lower peaks, or shoulders.” (Figure 2). Normal Head-and-Shoulders pattern is a bearish sign for the market that means the market will experience a price decline.

B—Inverted Head-and-Shoulders:

As in the price pattern, the Head-and-Shoulders pattern on MACD Histogram indicator can appear in the Normal Head-and-Shoulders form, as well as the Inverted Head-and-Shoulders form, defined as: The head is a ‘MACD Histogram’s Vertical Bars’ bottom surrounded by two higher bottoms, or shoulders.
From my experience, the Head-and-Shoulders pattern appears on the MACD Histogram indicator in most markets, independently of national exchange, and in all time frames.

The following are examples display developed markets like USA, UK, and France, as well as equities from several emerging markets, such as Egypt, Israel, Saudi Arabia, South Africa and Brazil. Some equities charts are for individual stocks and others are for market indices.

Additional examples will be provided from markets other than equities markets, such as commodities and currencies.

The pattern can appear on any time frame from the minute to hourly, to the daily, weekly and monthly charts. (The monthly period, however, requires a relatively long period for the pattern to develop and confirm.) We find this pattern appears on very old charts dating back to the 1900s when stock markets were still establishing themselves in North America (an example will be shown later for the Dow Jones in year 1907) and even in a more recent example such as the example of the Egyptian Stocks Index (EGX30).

Examples:

1—Developed Markets:

An example from developed markets is the British index (FTSE 100 Index, Fig. 7) illustrating how the Inverted Head-and-Shoulders pattern on the MACD Histogram lead a continuation pattern of a major move in mid 2009.

2—Emerging Markets:

The appearance of the Inverted Head-and-Shoulders pattern on the Egyptian stock (El-Ezz Steel Company, fig. 9) signaled the beginning of a retracement that lasted 11 consecutive sessions (11 vertical MACD Histogram bars) from the date of entering this trade in October 2008, generating around 15% profit at the exit point.
Our next example from the emerging stock market of Egypt is Orascom Telecom Holding (Fig. 10), which experienced a sharp increase in price by 22% in 9 days following the formation of an Inverted Head-and-Shoulders pattern on MACD Histogram indicator in mid 2009.

For the emerging markets in Middle East and Asia, we review a daily chart for the Saudi Index (Tadawul, Faig. 11) as an example. Figure 11 shows how the Inverted Head-and-Shoulders pattern lead the upward retracement in February 2009 and lasted for 10 consecutive trading sessions and resulted in 13% gain.

Israel Chemicals (Fig. 12) shows how the pattern repeated in the same cycle, resulting in terminating the original trend direction and shifting to the alternate direction, each time the Head and Shoulders of the MACD leading the directional move.

Israel Chemicals (Fig. 12): Israel Chemicals (ICL.TA) — Daily

Harmony Gold Mining listed on the Johannesburg stock exchange (Fig. 14) is an example from smaller or emerging markets of Africa. Here, we see the stock declined sharply after the appearance of the Normal Head-and-Shoulders on the MACD Histogram indicator.

The Sao Paulo SE Bovespa Index in Brazil (Fig. 14) moves upwards upon the appearance or trigger of an Inverted Head-and-Shoulders pattern in the beginning of 2004.

Harmony Gold Mining: Harmony Gold Mng (HARJ.J) — Daily

Sao Paulo SE Bovespa Index: Sao Paulo SE Bovespa Index (.TASI) — Daily
3—Currencies
An example from the foreign exchange market is the currency pair of Australian Dollar vs. U.S. Dollar (Fig. 15). This chart shows an Inverted Head-and-Shoulders with both shoulders separated from the head before the increase of the Australian Dollar over the USD by the end of 2007.

4—Commodities
In Figure 16 we see an example of the Head-and-Shoulders pattern on MACD Histogram indicator in commodities market. As we see on the chart, here too, the pattern signaled the onset of a significant decline for gold, starting in July 2008.

5—Time Frames
Daily charts were shown in the previous examples. The following are weekly charts from developed and emerging countries with the most recent example of the EGX30 at the end of 2009.

Figure 17 presents a weekly time-frame in a developed market. The Inverted Head-and-Shoulders sharply reversed the trend after its formation in October 2002. The stock’s price increased by 29% in 10 weeks.

An example in emerging markets from Israel. The formation of normal Head-and-Shoulders with the right shoulder separated from the head in March 2002 resulted in a decline in the stock’s price.

The weekly chart (Fig. 19) of last few weeks of 2009 shows how the Egyptian EGX30 index dropped following the formation of a Classic Head-and-Shoulders on the MACD Histogram indicator.
Trading the Pattern

First of all, we have to setup the MACD Histogram indicator that we will use on the chart. The default settings of the MACD Histogram indicator should be the same as the default set in Reuters charts, used as the source of data and charting.

MACD Histogram Settings:
- Short Periods: 12
- Long Periods: 26
- Signal Line Periods: 9
- Averaging Method: Exponential

In other charting systems, the settings may appear in different names, such as:
- Fast EMA (Exponential Moving Average): 12
- Slow EMA (Exponential Moving Average): 26
- MACD or Signal EMA (Exponential Moving Average): 9

Using Head-and-Shoulders patterns on MACD Histogram indicator

The Head-and-Shoulders pattern on MACD Histogram indicator helps the technical analysts determine potential market direction. The Normal Head- and-Shoulder pattern suggests that the following few days will be a declining market, while the Inverted Head-and-Shoulders form of the pattern suggests a rise in the market. Using the pattern to determine likely market direction in the near future is a simple, yet efficient application of this pattern. Another application is to use the described pattern as a confirmation indicator along with other technical analysis tools.

Additionally, this Head-and-Shoulders pattern on MACD Histogram indicator could be successfully traded.

We now present the trading techniques of this pattern followed by a detailed statistical analysis showing the accuracy of the Head-and-Shoulders pattern on MACD Histogram indicator.
Trading the Head-and-Shoulders pattern on MACD Histogram indicator starts by recognizing the pattern on the chart, as it is forming, which is never as easy as recognizing the pattern post its complete formulation. Following is a described method for trade entry during pattern formation:

Figure 21 shows how the pattern will look on the MACD Histogram vertical bars, while it is still forming in the case of a Normal Head-and-Shoulders pattern, as well as showing the entry bar to a trade.

Figure 22 shows the pattern on the MACD Histogram vertical bars, as it is forming in the case of an Inverted Head-and-Shoulders pattern. It also specifies the entry of the trade.

**Entering the trade**

After recognizing the Normal or Inverted pattern, one can see that entering the trade will always be from the right shoulder after spotting its peak. We will enter the trade during the formation of the right shoulder and before the pattern is completed. In the case of Normal Head-and-Shoulders pattern (Figure 21), the right shoulder’s peak is the highest vertical bar of the MACD Histogram indicator in the right shoulder, which is followed by another bar to its right that closes lower. This latter bar is considered a confirmation of the formulation of the right shoulder. This is the signal to enter the trade at the opening price of the following right bar. In short, entering the trade is made at the opening price of the second lower bar to the right of the highest bar of the right shoulder. A short (Sell) position will be made, as the market is expected to decline (Figure 23).

**Exiting the trade**

Exiting the trade does not differ from the entry methodology. Exiting the trade should be decided when a reversing bar is formed.

In the case of Normal Head-and-Shoulders pattern, where the slope of the bars is down, the signal to exit the trade will be a bar that reverses the slope to be an up slope. Once this happens, the exit should be made at the opening of the second bar to the right of the reversing bar (Figure 23).

In the case of Inverted Head-and-Shoulders pattern with an up slope, exiting the trade should be decided at the opening price of the second bar to the right of the reversing bar (Figure 24).

In Figure 23 we see a real case for the British Pound Sterling (GBP) by the end of 1996, where we can recognize a Normal Head-and-Shoulders pattern with the entry and exit points for a short (Sell) trade spotted on the chart. A drop in the price can be easily seen, which resulted in an approximate move of 3% of the entry price in 10 days.

In Figure 24 between September-October 1985 the chart shows General Electric stock forming an Inverted Head-and-Shoulders pattern on the MACD Histogram indicator. The entry of a long (Buy) position is shown in green. This position resulted in a return of approximate 3.7% in eight days as price increased following the formation of the pattern. The red line shows the bar at which the trade was closed.

**Stop Loss**

When should a trade be considered a failure? In other words, when should one exit the trade without making any profit or with minimal loss? Depending on the aforementioned understanding, one should expect a signal based on the movements of the vertical bars of the MACD Histogram indicator.

After entering a trade at the right shoulder and one of the following bars to the right of the entry bar moves in the reverse directions of the entry bar and the slope, we must first observe if the bars crossed the zero line to allow us to act according to the following cases:
1. If the bars cross the zero line, the exit should be made at the opening price of the second bar to the right of the reverse bar (Figure 25).
2. In case the bars did not cross the Zero line, but the slope is reversed:
   a. One should wait until the new bars exceed the highest or lowest bar of the right shoulder (depending on whether it is a Normal or Inverted Head-and-Shoulders pattern). When a bar closes higher than the peak, or lower than the bottom, of the right shoulder, the trade must be closed at the opening price of the following bar to the right (Figure 26).
   b. Otherwise, the pattern may be forming a second right shoulder that is shorter than the first right shoulder (i.e. does not exceed the first right shoulder). In this case the pattern should be treated as if it has only one right shoulder (Figure 27).

In some cases after exiting the trade, one can find the bars reversing again. In this case, we consider the new reverse a second taller right shoulder, and we can re-enter the trade again, if we see the usual entry signal on the second right shoulder (Figure 28).

---

**Statistical Analysis of the Head-and-Shoulders Pattern on the MACD Histogram Indicator**

Here the daily charts of Dow Jones Industrial Average (DJIA), General Electric Stock (GE), Silver and British Pound Sterling (GBP) for the period between January 1983 and December 2009 for conducting this statistical analysis are used.

During the specified period mentioned above, sixty-seven Head-and-Shoulders patterns appeared on the MACD Histogram indicator in all the four investment products under examination in this analysis.

The pattern appeared 19 times on each one of the DJIA and the GBP. In 79% of the DJIA’s cases the pattern was a success, while the success rate for the GBP was 84%. On the charts of the General Electric Stock, the pattern appeared 17 times and succeeded in 82% of the cases. The lowest success rate was 75% of the 12 cases that appeared on Silver charts.

Out of the total 67 appearances of the Head-and-Shoulders pattern on the MACD Histogram indicator, the pattern was successful in about 81% of the cases (54 times), while it failed in 19% (13 times). This means, that the success rate of the pattern is more than 4 times the rate of failure, indicating a very high statistical significance of the accuracy of the Head-and-Shoulders pattern on the MACD Histogram indicator.
The Normal form of the Head-and-Shoulders pattern appeared 33 times, representing 49% of the total 67 appearances of both forms of the pattern, while the remaining 51% represents the 34 incidents, in which it appeared in the Inverted form.

In 24 out of 33 cases, the Normal form of the pattern was profitable. The 88% success rate of the Inverted form of the pattern presents 30 cases of success out of 34 appearances in all of the four investment products. The largest portion of successful patterns were seen in the DJIA at 100%, as 13 out of 13 Inverted patterns founded on the DJIA were successful cases (Figure 34). GBP had the most number of appearances with a success rate of 85% of the 13 appearances of the Normal patterns (Figure 35). Inverted Head-and-Shoulders pattern proved to be the most successful form of the pattern and of very high statistical significance.
Fifty nine percent of all successful trades in all the four investment products together fall in the profit bracket of 1% to 3%, when using the trading method explained earlier in this paper, while the remaining 41% gains are more than 3%. Using the same method, we find that the majority of losses are less than 1% with a rate of 77% of unsuccessful trades. Just one case out of the 13 unsuccessful trades recorded a loss of 4.7% (in Silver), which is the highest loss rate recorded among all cases. One out of the thirteen failures was a breakeven at the specified exit point of the trade. Successful trades generated on average 4% profit per trade. The average loss per unsuccessful trade was 0.91%, which is much lower than the average profit. Approximately 2/3rds of successful trades generated more than 2% profit. The highest profit percentage was 23%, recorded in Silver (Figures 36 and 37).

Half of the successful trades in General Electric stock generated profits up to 3% and the other half more than 3% gain, while 100% of the unsuccessful trades had a loss rate of less than 0.6%. General Electric recorded its most successful trade during the period under examination in November 1989, when an Inverted Head-and-Shoulders pattern preceded a price of the stock to gain 12%, while the lowest profit percentage during the same period was recorded two times in February 2007 and August 2008 with a 1.2% percent profit. On average, and following the pattern indicator, General Electric gained 4.2%, while it lost an average of 0.28% per unsuccessful occurrence of the indicator. (Figure 39).

Throughout this statistical analysis, Silver proved to be the most volatile among all the four investment products under examination with profit percentages distributed among many categories. Silver recorded the highest profit percentage per trade among all the investment products when it gained 23% profit in September 2008, as well as the greatest loss rate of 4.7% in November 1983. Average profit percentage for Silver is 7.9% per trade and average loss per trade is 1.9% (Figure 40).

The British Pound Sterling (GBP) proved to be the most interesting investment product under examination. It was the most consistent in terms of profit/loss percentages with the least extremes as compared to the other three investment products. Eighty eight percent of the successful trades generated 1% to 3% out of which 65% fall between 1% and 2%. Its highest profit percentage, after appearance of the indicative pattern, was in April 1985 with a rate of 4.8%, while lowest profit rate was 1%, and was recorded in seven cases. Its worst loss was 1.9% in June 1988 and the average loss per trade was 1.2% in only three unsuccessful trades. On the other hand the average profit in 16 winning trades was 1.87% per trade (Figure 41).
Duration of trading the Head-and-Shoulders pattern on the MACD Histogram indicator from entering the trade position until exiting it is an additional and important consideration. The average duration per trade was around eight vertical bars of the MACD Histogram bars, which represents eight days in this statistical analysis. As we know each bar of the MACD Histogram indicator represents one bar on the price side of the chart. This price-side bar can represent a minute, an hour, a day, a week or a month depending on the time-frame used for the chart.

In figure 47, we see that almost 70% of the trades lasted between seven and 10 days, with the highest rate of occurrence for the seven days duration, representing 26% of the total number of successful trades. Second to this comes the 10 days duration with 18% of all successful trades. Each of the four investment products, separately, ranged between eight and 8.6 days of duration on average, which is around the average duration mentioned above. Five days was the lowest number needed to complete a winning trade for the period and investment products under examination. There was no trade found to last less than five days or more than 14 days. One case in each investment product lasted five days, while the 14 days duration was recorded only twice, once in DJIA and the other in General Electric Stock (Figure 42).

If this methodology is applied on weekly charts, it is expected to generate greater gains in percent profit. Larger percentage profit require longer durations and when considering weekly charts, each vertical bars of the MACD Histogram indicator represents one week in this statistical analysis.

**Risk/Reward Ratio**

According to the methodology of trading the Head-and-Shoulders pattern on MACD Histogram indicator and to the findings of the statistical analysis, if we take the average gain of 4% per trade and divide it by the average loss of 0.91%, we have a positive risk/reward ratio of 4.4.

**Conclusion**

This paper—supported by the results of the statistical analysis—demonstrated that the Head-and-Shoulders patterns appearing on MACD Histogram indicator can be used to make long or short trading decisions in any liquid market or investment product. Indicators are usually used as supporting tools to confirm a trade entry and/or exit, but this paper demonstrated, that the MACD Histogram indicator and associated Head and Shoulders pattern formation can also be used to help allocate a specific entry/exit point of a trade.

The statistical analysis conducted strongly indicates that the methodology applied to trading offers an expected risk to reward ratio of 4.4. In addition to the very good risk to reward ratio, the analysis showed that failures counted to less than 20% of total frequency of appearance of the pattern, which also represents only 24% of the 54 winning cases. This means, that each time the pattern is traded the expected rate of success, including the percentage profit, is statistically significant.

On the daily period under statistical analysis, the pattern proved to generate acceptable average profit percentage per trade in a relatively short period of time under consideration, which amounted to an average of eight days per trade. This is considered acceptable duration relative to the profit outcome.

The Head and Shoulders pattern as applied to the MACD may be used as a predictive trading indicator to the long or short side in liquid markets and under various time frames.

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**Software and data**

Data and charts provided by Reuters

Dow Jones chart example of the year 1907 provided by Prophet.net

**Endnotes**


2 Elder, Alexander, Trading for a living, Wiley, 1993. Pg. 102
Trading Strategies Based on New Fluctuation Tests
by Daniel Ziggel (daniel.ziggel@quasol.de) and Dominik Wied (wied@statistik.tu-dortmund.de)

Abstract
There are many empirical hints that correlations and variances among many time series cannot be assumed to remain constant over longer periods of time. In particular, correlations and variances among stock returns seem to increase in times of crisis. An increase of correlations and volatilities has serious consequences for diversification effects, which lie at the heart of several applications in risk management and portfolio optimization. In this paper, we analyze recently proposed tests to determine if correlations and variances of assets are constant over time. An empirical application to various assets and trading strategies suggests that the tests perform well in practice.

Introduction
During the recent financial crisis, capital market volatilities and correlations increased quite dramatically. As a consequence, risk figures increased significantly, diversification effects were overestimated and ultimately, capital was lost. In literature, this phenomenon is sometimes referred to as "Diversification Meltdown" (Campbell et al., 2008). Moreover, there is a consensus in empirical finance, that market parameters cannot be assumed to remain constant over longer periods of time (e.g. Krishan et al., 2009). In particular, the relevant parameters seem to increase in times of crisis. A comparison of correlations and volatilities during different market phases in the last ten years can be found in Bissantz et al. (2011a, 2011b).

A diversification meltdown has serious consequences for applications in finance. For example, portfolio optimizations which are based on diversification effects between several assets are no longer valid if the parameters changed. Similar problems occur with applications in risk management or for the valuation of financial instruments. Surprisingly, there is a lack of methods to formally test for changes in correlations or volatilities as most existing procedures either require strong parametric assumptions (Dias and Embrechts, 2004), assume that potential break points are known (e.g. Jennrich, 1970), or simply estimate correlations from moving windows without giving a formal decision rule (e.g. Longin and Solnik, 1995). Only recently, Galeano and Peña (2007) and Aue et al. (2009) have proposed formal tests for a change in covariance structure, which do not build upon prior knowledge as to the timing of potential shifts. The test of Aue et al. is based on cumulated sums of second order empirical cross moments (Ploberger et al., 1989) and rejects the null of a constant covariance structure if these cumulated sums fluctuate too much, while Galeano and Peña work in a parametric environment.

In this paper, we use tests proposed by Wied et al. (2011a, 2011b) which focus on correlations and volatilities in order to derive trading strategies. Moreover, we analyze the dates of rejection and the resulting parameter estimators. It turns out that the tests perform very well throughout the whole empirical application and the resulting dates of rejection seem to be reasonable. Additionally, the resulting trading strategies seem to be promising.

Model and Test Statistics
Let \( (X_t, t = 1,2, \ldots) \) be the time series of an asset. For example, \( X_t \) might be the final quote of day \( t \). We want to determine whether the variance of \( X_t \) is constant over time, i.e. we test:

\[
H_0: \text{Var}(X_t) = \sigma^2 \quad \forall t \in \{1,2, \ldots, T\} \quad \text{vs.} \quad H_1: \exists t \in \{1,2, \ldots, T-1\}: \text{Var}(X_t) \neq \text{Var}(X_{t+1})
\]

Here, \( \sigma^2 \) is assumed to be constant. The test statistic is given by:

\[
V_T(X) = \max_{1 \leq j \leq T} \frac{\bar{D}}{\sqrt{T}} \left( \frac{\text{Var}X_j}{\text{Var}X_1} - 1 \right)
\]

The test rejects the null hypothesis of constant variance if the empirical variance \( \text{Var}X_j \) fluctuates too much. The fluctuation is measured by \( \max_{1 \leq j \leq T} \left( \frac{\text{Var}X_j}{\text{Var}X_1} - 1 \right) \). The weighting factor \( \frac{\bar{D}}{\sqrt{T}} \) scales down deviations at the beginning, where the fluctuations are more variable. Besides, the scalar factor \( \bar{D} \) is required to derive an asymptotic distribution under the null and is cumbersome to write down, but can easily be calculated from the data. The complete formula can be found in Wied et al. (2011a).

Under some mild theoretical conditions, the asymptotic null distribution of the test statistic is a one-dimensional Brownian bridge. This distribution is well known (Billingsley, 1968). Using the quantiles of this distribution, we obtain an asymptotic test for our problem.

The test for constant correlations is quite similar. Nevertheless, we need two time series \( (X_t, t = 1,2, \ldots) \) and \( (Y_t, t = 1,2, \ldots) \). With this, the test statistic is given by:

\[
C_T(X,Y) = \max_{1 \leq j \leq T} \frac{\bar{D}}{\sqrt{T}} \left( \frac{\text{Corr}X_jY_j}{\text{Corr}X_1Y_1} - 1 \right)
\]

The expression \( \text{Corr} \) is the empirical correlation coefficient calculated from the first \( k \) observations. The test rejects the null hypothesis of constant correlation if the empirical correlations fluctuate too much, as measured by \( \max_{1 \leq j \leq T} \left( \frac{\text{Corr}X_jY_j}{\text{Corr}X_1Y_1} - 1 \right) \). Again, the weighting factor \( \frac{\bar{D}}{\sqrt{T}} \) scales down deviations at the beginning, where the fluctuations are more variable. Moreover, the scalar factor \( \bar{D} \) captures the volatilities of \( X_t \) and \( Y_t \) as well as the dependence of \( (X_t, Y_t) \) over time in order to derive the asymptotic null distribution. As before, the asymptotic null distribution of the test statistic is a one-dimensional Brownian bridge. The complete formula can be found in Wied et al. (2011b).
Test Procedure

As mentioned above, quantiles of the asymptotic distribution can be found in related reference books. Popular quantiles are given by:

- 1.073 (80%)
- 1.224 (90%)
- 1.358 (95%)
- 1.628 (99%)

For example, if \( C_T(X) > 1.358 \), we can reject the null of constant correlation on the significance level 5%. Roughly spoken, the correlation has changed with a probability of 95%.

Consequently, the significance level has to be chosen carefully in practical applications. The lower the significance level is chosen, the earlier and more sensitive the test reacts and the other way round. Our empirical results suggest that \( \alpha=5\% \) is a reasonable choice for a lot of applications.

Besides, large differences of the market parameters between the break points can be observed hinting at a reasonable separation of different market phases. This phenomenon provides the basis for our trading strategy described in the next section.

Table 1 illustrates this phenomenon for the DAX and shows the annualized market parameters (returns and volatilities) for the respective period between two structural breaks.

### Table 1: Structural breaks (Volatilities, \( \alpha=5\% \))

<table>
<thead>
<tr>
<th>S&amp;P</th>
<th>DAX</th>
<th>REX</th>
<th>CRB</th>
</tr>
</thead>
<tbody>
<tr>
<td>03.02.1988</td>
<td>29.01.1988</td>
<td>12.02.1990</td>
<td>15.03.1988</td>
</tr>
<tr>
<td>05.02.1988</td>
<td>28.10.1988</td>
<td>06.06.1994</td>
<td>03.06.1988</td>
</tr>
<tr>
<td>30.09.1993</td>
<td>01.02.1989</td>
<td>01.05.1995</td>
<td>02.02.1990</td>
</tr>
<tr>
<td>10.03.1997</td>
<td>07.06.1989</td>
<td>19.02.1996</td>
<td>05.08.1994</td>
</tr>
<tr>
<td>28.10.2008</td>
<td>14.03.1994</td>
<td>14.05.2001</td>
<td>19.05.1998</td>
</tr>
<tr>
<td>09.01.2009</td>
<td>19.08.1997</td>
<td>01.08.2003</td>
<td>18.06.2001</td>
</tr>
<tr>
<td>27.01.2002</td>
<td>22.03.2002</td>
<td>18.10.2004</td>
<td>19.10.2001</td>
</tr>
<tr>
<td>17.09.2003</td>
<td>06.02.2004</td>
<td>29.02.2008</td>
<td>23.05.2003</td>
</tr>
<tr>
<td>14.07.2006</td>
<td>07.03.2005</td>
<td>27.01.2010</td>
<td>23.06.2003</td>
</tr>
<tr>
<td>06.10.2006</td>
<td>06.11.2007</td>
<td>24.11.2008</td>
<td>21.07.2003</td>
</tr>
<tr>
<td>14.03.2007</td>
<td>28.08.2009</td>
<td></td>
<td>10.05.2004</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>02.09.2008</td>
</tr>
</tbody>
</table>

Structural Breaks

In order to evaluate the quality in applications, the tests are applied to several time series of assets: two stock indices (S&P 500, DAX), a commodity index (CRB Spot Index) and a government bond index (REX), using daily data (final quote) and a time span of 22 years (January 1988 to April 2010).

The procedure for the test is as follows. We start at the 20th available data point and increase the period of time successively for one day. The starting point is due to the fact that approximately 20 data points are required for a reliable estimation of the respective parameter. This procedure is performed until the test rejects the null hypothesis of constant correlation resp. variance. Then, the 20th day after rejection is the new starting point and the procedure is repeated for the remaining time span. This procedure is due to the fact that the parameter can no longer be assumed to be constant, if the null hypothesis is rejected. A new reliable estimation requires once again 20 data points after the point in time, where the parameter changed.

Otherwise, the estimator would be biased as data of two different phases were mixed.

Tables 1 and 2 include the rejection dates of the null hypothesis for the significance level \( \alpha=5\% \). The results seem to be reasonable. Moreover, there is a strong dependence between structural breaks and distinctive changes in trends. For example, there are a lot of rejections between 2000 and 2003 (Dotcom-crisis) and in 2008 (financial crisis). In contrast to that, there are only a few structural breaks in stable market phases.

Our results show that the chosen significance level plays an important role for both rejection frequency and rejection dates. Consequently, the significance level has to be chosen carefully in practical applications.

### Table 2: Structural breaks (Correlations, \( \alpha=5\% \))

<table>
<thead>
<tr>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>22.11.2000</td>
<td>15.10.2002</td>
<td>11.03.1999</td>
<td>28.06.2002</td>
<td>23.09.2008</td>
<td>05.05.1998</td>
</tr>
<tr>
<td>20.12.2000</td>
<td>01.08.2003</td>
<td>09.10.2008</td>
<td>17.03.2008</td>
<td>15.08.1998</td>
<td>15.06.1998</td>
</tr>
<tr>
<td>07.01.2003</td>
<td></td>
<td></td>
<td>14.10.2008</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25.03.2003</td>
<td></td>
<td></td>
<td>11.11.2008</td>
<td></td>
<td></td>
</tr>
<tr>
<td>22.02.2008</td>
<td></td>
<td></td>
<td>09.12.2008</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
test, we perform an out of sample study. In this study, we investigate a simple strategy which applies the proposed test.

The strategy is as follows. The available time span since the last detected change in volatility is used to calculate the historical return, which is used as an estimator for the future. Moreover, an asset is allowed to be bought if the last structural break lies 20 days or more in the past and the return estimator is positive. A short position is opened, if the last structural break lies 20 days or more in the past and the return estimator is negative. Finally, the capital is uniformly allocated between all allowed assets.

In order to guarantee an objective back-test, we assume the following:

- The test is performed daily (final quote).
- Portfolio shifting is done the next day (final quote).
- We neglect transaction cost, taxes, fees and currency fluctuations.
- The rebalancing is performed daily.
- The significance level is \( \alpha = 5\% \).

Note that the strategy is based on indices, which can be implemented by means of ETFs and ETCs. Hence, transaction costs play only a marginal role. We use the following indices for our strategy:

- EuroStoxx 50 (Long & Short)
- MSCI Emerging Markets (Long)
- Gold - troy ounce (Long)
- iBoxx euro zone 3-5 Years (Long & Short)

The choice is due to two reasons. On the one hand, the investment universe should be simple and clearly arranged. On the other hand, there should be different instruments available in order to react to various market phases. This is guaranteed by means of six allowed trading options. These options cover increasing and decreasing stock markets and interest rates. Moreover, commodities protect against rising inflation. Hence, a lot of different scenarios can be covered. Finally, all indices can be implemented by means of ETFs and ETCs.

**Results**

We will only present results for the trading strategy, which is based on structural breaks of volatilities as the results are quite similar for the strategy based on correlations. The results can be found in Table 4 and Figure 1.

The strategy yields an above-average return in comparison to the underlying indices. Moreover, the portfolio development is very smooth—even throughout financial crisis. This result is remarkable as three risky assets are used within the strategy.

### Application Areas

Before describing our trading strategy in detail, we want to present several application areas of the tests. When developing the tests, we first wanted to find optimal time points for the re-optimization of a portfolio, i.e. we wanted to use the tests for an optimal timing. A re-optimization is necessary if the input-parameters (correlations or volatilities) change significantly so that parameter estimation and portfolio optimization based on data points before the structural break would then no longer be valid.

Another potential application is the implementation of an alert-function. For example, if an unfavorable parameter changes occur, warnings for risk management are generated. With the help of such an alert-function, also estimation of measures like the value-at-risk might be improved. In addition, as explained previously, the operator can detect trends, which might be visualized by turning lights. Importantly, whole trading strategies basing on structural breaks can be developed.

### Trading Strategy

The results above show that changes in market parameters can reasonable be detected. In order to investigate the possibility to derive trading strategies, which are based on the proposed

### Table 4: Results of the trading strategy and summary statistics

<table>
<thead>
<tr>
<th></th>
<th>Strategy</th>
<th>EuroStoxx 50</th>
<th>MSCI EM</th>
<th>Gold</th>
<th>iBoxx euro zone</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return p.a.</td>
<td>10.16%</td>
<td>-0.15%</td>
<td>10.45%</td>
<td>12.77%</td>
<td>4.01%</td>
<td>6.77%</td>
</tr>
<tr>
<td>Volatility p.a.</td>
<td>10.02%</td>
<td>22.47%</td>
<td>17.24%</td>
<td>17.99%</td>
<td>2.59%</td>
<td>15.07%</td>
</tr>
</tbody>
</table>
Compared to average values there is a significant improvement of the relevant parameters. More precisely, the return increases by 50.07% whereas the volatility decreases by 33.51%. The Sharpe Ratio is about 1—also a good value.

Figure 2 shows the development of portfolio weights over time. Between crises, the weights are very stable whereas in times of crises a lot of fluctuations can be observed. This fact guarantees the good performance and the prevention of (high) losses during financial crisis.

We want to point out that alternative and more sophisticated strategies can easily be constructed by means of the fluctuation tests. However, we consciously chose this simple and traceable strategy in order to demonstrate the principle and benefit. As this simple strategy yields already remarkable results, we expect a refinement of the strategy to improve the results even more.

Conclusion and Outlook

In this paper, we have described two new tests to determine whether correlations and variances of time series are constant over time and have investigated their performance in several applications. To this end, we have applied the tests to several time series of assets which are relevant for applications in finance and have found that the tests perform well in these applications. Moreover, we have derived a simple trading strategy and have proved its usefulness by means of an out-of-sample study. For sake of simplicity, we have tried to avoid mathematical details and cumbersome formulas.

Nevertheless, some fundamental questions still remain: It is of interest to specify the economic determinants of fluctuations to model and forecast variations of correlations and variances. And the question arises if parameter estimators, based on the new tests, will improve the performance of portfolio optimization. Portfolio optimization depends, of course, on a reliable estimation of market parameters. These topics will be in focus of our ongoing research.

Acknowledgements

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References

Abstract
A short review of the principles behind W.D. Gann’s work on Time Cycles and examination of the phenomenon seen behind these cycles on three equities, including Skandia, Ericsson, Astra Zeneca and the Nasdaq100.

Introduction
This paper will attempt to demonstrate an implausible phenomena: one that moves us to contemplate about how precisely the markets do, indeed, vibrate through time.

This will be my interpretation of one aspect I have studied on W D Gann’s large work, where the major sources are what I have learned from my Swedish teacher Ingemar Carlsson, who showed me this form of analysis for the first time in 1998, and my Australian/American teacher Bill McLaren, of whom I have been a student since 2000. Both of these gentlemen are still my biggest source of inspiration and new insights.

Please also note that Gann Analysis is just one of several tools I use for technical analysis. I have found the pattern of trends and what actually is on the chart, to be the basic and most important element to construct an analysis of a stock. To this we can add volume analysis, indicators, intra-market analysis, wave theory, Fibonacci, etc., and time analysis.

This text does not claim to be a full description of W D Gann’s time cycles. Instead, my intention is to give the reader some insight to the interest and value of Gann Theory, with a brief theoretical introduction and a few thorough examples to hopefully evoke a curiosity and desire for further studies.

The Yearly Cycle
As a fresh student on Gann’s time factor, I think the Yearly Cycle is the best time consideration to start one’s studies. This is because we all can relate to the year as a cycle and then the seasons within that particular cycle. Additionally the yearly cycle presents common phenomenon for many of the world’s indices, stocks, currencies etc.

A year consists of 365 calendar days, but to give our analysis some margins of order and consistency, we shall define every month as 30 days, and therefore the year in this analysis contains only 360 days. As we all know, a circle consists of 360 degrees, so now we can look at the Yearly Cycle as a circle with its 360 degrees (days) in its full revolution. This method will make our study more instructive.

In both his time and price analysis, Gann divides the cycles and movements into 1/8’s and 1/3’s and their multiples and divisions, to determine the divisions of the cycles. See figure 1, and note the division of the Yearly Cycle: Dividing 360 days by 2, gives us 180 days, and dividing this again by 2 gives us 90 days, which of course also is 360 days divided by 4. If we again divide by 2 we get 45 days, which as we know is 1/8 of 360 days.

Dividing 360 days into 1/3’s gives us 120, 240 and 360 days in the yearly count. And from the 1/8 and 1/3 divisions together, we can derive the divisions by months, or 30 days, 60 days and 90 days etc. We now make a division in the circle so that we can
place it along the x- or time axis on the chart as shown in figure 2.

Continuing in this analysis, we then count the days from determined significant highs and lows to identify if the particular cycle at hand is valid. However, we do not expect to see exact reactions at every single date we think might be important. Instead, we “Use them as a road map to measure the duration of moves and also as general time periods to look for more significant changes in direction”, as McLaren expresses it describing the day counts.

For example, suppose a stock has been trending down for many months, however in recent time with decreasing momentum (see figure 3). In our illustration, on the 21st of December the stock reaches a low and starts to trade up for three weeks before declining again, but this time reaching a higher low on the 21st of January. That the stock has made a higher low is as we all know and possible sign that it could be going from the falling trend to something else (in addition to the stock breaking the falling trend line). But because it is exactly 30 days between these two lows, we now also have a sign that the stock might have started to vibrate with the Yearly Cycle.

During the following two months, the stock trades up and down in a base pattern, making yet another higher low on the 21st of March, exactly 90 days after the first significant low. Such an observation would be additional evidence that the stock has started to vibrate with the Yearly Cycle. Then breaking obvious resistance, the stock takes off in a rally. After a period of time, in this illustration, it then reverses into 135 and 150 days from low, indicating further gains on the upside, after which the stock exhausts up into 180 days from low on the 21st of June, signalling a possible high or at least significant resistance in time. This was one example and illustration of how time cycles could be set-up based on the above price progression theory.

Does this work in practice? To explore and answer this question we will review examples from the financial markets, most of which I have followed in real time as they unfolded through time. The following examples have been prepared for various lectures held at the University Of Lund, Sweden, and other venues over the last years. Added to this is a recent example observed in the Nasdaq-100, which the reader can continue to monitor from the analysis given here.

**Skandia**

Let’s turn to figure 4, the Swedish insurance company Skandia, during 2001-2004 (since acquired by Old Mutual). At a first glance there doesn’t appear to be a particular cyclical pattern on this chart, but instead more an irregular chopping up and down price action. If we zoom in the development from the significant high in February of 2004 where Skandia turned into a creeping trend to the downside, and look at that a bit more closely, we find a very precise pattern.

![Figure 3](image)

**Figure 3**

![Figure 4](image)

**Figure 4**

We will allow +/- 1 day at the dates for the cycle turning points, to give the analysis margin. This is one method of various techniques. As we are working with calendar days it follows that if the expected turning point will occur at a weekend, we must allow the turning point to occur during the trading sessions both at the Friday before or the Monday after that particular date. The following weeks of trading can then give a clue on which date actually was the date from a cyclic perspective.

![Figure 5](image)

**Figure 5**

Viewing figure 5, we note that Skandia reached an important high on the 13th of February 2004, after which it went into a creeping downward trend. This day was a Friday, so the cyclical...
top could have come from the Thursday before, to the Monday thereafter. As we see by the chart, the following months of trading would, however, suggest that the cyclical top came in at the Monday, on the 16th of February. We’ll soon discover why this is so.

Observing three months later, we find that a low was established in mid May, or more precisely on the 17th (Monday), indicating a cyclical low between the 14th (Friday) and 18th (Tuesday). This is approximately 90 days after the top in February, so a possible Yearly Cycle present.

Another three months later a new significant low was established in mid August, on Monday the 16th to be exact. The cyclical low should be between the 13th (Friday) and the 17th (Tuesday) of August, or 90 days from the May low, and of course 180 days from the February high. The stock traded 90 days high to low, and then 90 days low to low. Looking 90 days ahead from that time period, we find that Skandia reached a new high on Monday the 15th of November. The trend was now once again about to change to an upward trend after 10 months, so not a large reaction in price this time.

But let’s go back to study these 10 months in more detail. So far we notice how a very precise 90 day cycle is marked by important highs and lows during this time period. But there are other significant turning points on the chart. Are they somehow linked to this rhythm?

Half of the 90 day cycle is 45 days, which is 1/8 of 360 days. Having discovered a very accurate 90 day cycle, let’s continue our research to see if we can find 45 day increments within those 90 day vibrations. Adding 45 days from the top on the 16th of February gives us early April as a probable turning point. The chart confirms our theory (figure 6). The stock has made a lower high on the 5th of April which was a Monday; and we conclude that Friday the 2nd of April in fact is the cyclical turning point. Indeed, Skandia then falls another 45 days in to the 90 day bottom on the 17th of May as can be seen on the chart.

Figure 6

From that date the stock starts to rise for 45 days again, into another lower high on Friday the 2nd of July. Note that it follows that this is then 90 days from the first lower high at the 2nd of April, and 135 days from the top price where this moved initiated. Naturally, there is then 45 days to the next 90 day low in mid August, which we identified earlier. As we see, this low is 45 days from high, 90 days from low, 135 days from high and 180 days from the top. We have observed here the accuracy of the 45 day cycle within the 90 and Yearly Cycle.

As we see by the chart, the next move up from the 16th of August lasted another 45 days, bringing in another lower high on Monday the 4th of October at the falling trend line. That Monday is within the defined time window, Friday/Monday, and as we see, it produced the high for another run down and a double bottom some three weeks later in late October. Another 45 days later, and 90 days from the low in August, yet another lower high was established within the falling trend line and resistance, on the 15th of November. At this point however, pattern of trend had started to indicate to us a possible change in trend which was confirmed by the break of the trend line a few weeks later. This started a new uptrend, but the 45 day cycle continued to show some presence for yet some time. Look another 45 days ahead, and see how it brought in and fits an Elliott wave three high and reversal for two weeks.

Now go back to figure 4 on Skandia and we can see and conclude that in what seemed to be nothing more than an irregular pattern, was instead a very precise 45 day cycle present.

Ericsson

Let’s turn back the clock … and look at Ericsson, a company that has been of great economic importance in Sweden. During the euphoric era of that late 1990s to 2000, and after having performed very well for a number of consecutive years, Ericsson’s stock, which was the most heavily traded equity on the Stockholm Stock Exchange, exhausted up to it’s final top in March of 2000 (figure 7).

Figure 7

After reaching a top and all-time high at 117 Swedish crowns, on Monday the 6th of March 2000, Ericsson went into a topping formation for over six months, after which it started a severe decline reaching a final bottom in September of 2002 at 2.96 crowns(!!), at which point there was doubt about the company’s ability to survive. The final top and all-time high is obviously a very significant top for Ericsson, so let’s begin from there and
see if we can find a Yearly Cycle.

**Figure 8**

Monday the 6th was the top, so either of the days from Friday the 3rd thru Tuesday the 7th, is the possible start of a new cycle (figure 8). Going 30 days ahead to early April; we see reactions in the stock both at the 3rd (high) and the 5th (low). Another 15 days later looking for a possible 45 day reaction, we find a new low on Monday the 17th of April. It is maybe a bit early but still interesting to note at this point. This proves to be the start of a new two week 36 percent rise up to two lower highs on the 2nd and 5th of May (Tuesday after holiday and Friday), that is 60 days from the top in March. At the beginning of June, or 90 days from the top, Ericsson reaches another lower high on the 5th (Monday), which is then broken by marginally higher prices on the 8th (false break), followed by a 20 percent drop the rest of the month. The 120 day period from the high produces no significant turning point. But then on the 17th of July (Monday), 90 days from the April low we get another high, followed by a fast drop down until the 3rd of August, or 150 days from high. The stock then continues to trade around that low and is held down both on the 4th (Friday) and the 7th (Monday) developing a short term base pattern, from where it takes off up again and rises 26 percent in 30 days up to 180 days from high on the 5th of September (figure 9).

**Figure 9**

This lower high after 180 days is interesting because 180 is a strong vibration point within the Yearly cycle. Here, Ericsson gives a signal of another reversal move down. But looking at the pattern of trend, this could also be a possible end to a topping formation and the start of a downtrend, after having traded one 180-day and two 90-day cycle blocks, producing lower highs at their expirations. This is then confirmed by the break of obvious support in late September as seen in figure 9.

As an aside: In a downtrend, a counter trend reversal up into an important time period indicates resistance in time and price, with possible more to come on the downside. Likewise, in an uptrend, a counter trend reversal down into an important time period signals support in time and price, and that further gains may be expected.

With Ericsson, and from the top in early September the stock falls quite dramatically but reverses up in early October, producing a lower high on the 5th (e.g. 30, 120 and 210 days from high) after which it starts to fall again. In the second half of October Ericsson begins its reversal again — producing another lower high on Friday the 3rd of November (time window 60 days from September the 5th). Ericsson continues to fall, repeating the price action with a reversal up at the end of the month producing yet another lower high on December the 5th.

Once again, this is 90 days from the September high, 180 days from the June high and 270 days from the top in March, indicating resistance in time and that the downtrend could continue. Note also the reversal up to the 17th of October, 90 days from high and 180 days from low.

Looking another 90 days further (figure 10) we see the stock reversing up into the 4th of January (e.g. 30 and 300 days), Friday the 19th of January (e.g. 45 and 315 days) and the 6th of March (e.g. 90 and 360 days). This high in March is exactly one year from the top and completes the Yearly Cycle. This cycle continues, however, to influence price reactions in Ericsson, although weakened and not as exact as the earlier cycle phase identified.

**Figure 10**

I have marked some dates and turning points in figure 10 and 11, for the reader to examine, but if we just take a look at how the 90 day vibration continues to vibrate, we determine small reversals up to the 5th and 6th of June and the 4th of September.
2001, but not decisive and questionable from an analytical or practical trading perspective.

On the 6th of December 2001, however, Ericsson makes a very significant top again, followed by a continued downtrend, a clear reversal in late February and a lower high on the 7th of March 2002, two years from the top (with the time window extended to +/-2 days), indicating possible further declines. The downtrend proceeds, however, with no significant reaction in June during this cycle phase. In early September another lower high is reached on the 6th at around 7 Swedish crowns, followed by a final decline to the ultimate bottom at 2.96 crowns on the 30th of September 2002.

We have followed Ericsson down through the severe decline experienced during from 2000 – 2002; and observed how accurate the Gann Yearly Cycle vibrated through time, and the signals generated. Ericsson is one of the largest and most traded stocks at the Stockholm Stock Exchange, and every time I go through this example I ask myself how much of the capital, or better said the people behind it, are and were actually aware of these cycles. My guess is very, very few.

**AstraZeneca in 1999 - 2000**

In the next example, AstraZeneca, we will look at a time period where the Yearly Cycle was in force. AstraZeneca is a global biopharmaceutical company.

Ingemar Carlsson, mentioned in the introduction, showed me this form of analysis for the first time in 1998, so back in 1999 I had just started experimenting with these cycles trying to understand what to look for and what to expect from different setups. At this time, I was closely watching AstraZeneca (figure 12) trending up from the bottom on the 26th of July 1999 (Monday) reaching a temporary top on the 25th of August, and nearly repeating that pattern of a temporary high (resistance in time) a month later, or 60 days from low. The counts where not exact and I struggled here, trying to find indications of the presence of a possible Yearly Cycle. I anyway decided to monitor the stock more closely the coming months. The high on the 21st of October made me even more confused without a significant high or low around the 24th – 27th in October as expected. Later, I realized that AstraZeneca had produced a significant top 120 days from the low on the 24th of November 1999, and had started to trend down again. With this, I understood that a cyclical pattern could be unfolding and deserving of attention.

Just before Christmas on the 22nd and 23rd of December, and 30 days from the high, AstraZeneca produced a temporary low (support in time), and then a lower high on the 10th of January 2000 (Monday) or 45 days from high. Later in January another temporary low came in 60 days from high on the 25th of January, followed by a reversal and then a subsequent continuation of the downtrend.

In mid February AstraZeneca was still trending down and approaching the levels to around 290 SEK where it had bottomed seven months earlier before it started to trade up for 120 days. The 90 day time window around the 24th of February was going to be an important date from a cyclical perspective. If it provided a low, it could mark a possible change in trend, leading to a more significant move up. So my excitement grew day by day as the stock continued down. In addition to this, the company was going to report the 1999 year result on that very day. I emailed Ingemar to see if he had seen the setup with the 120 day move up from August to November and then the 30, 45 and 60 day increments on the way down from the November top.

“**Yes, I’m monitoring this myself, doesn’t it look beautiful? It sure looks as though AstraZeneca is going down into that date to produce a low, but as I have told you before we must wait until the cycle’s turning point to see if we really get a low established. As you know by now, there is also a chance we will get another lower high and a continuation of the downtrend. The best thing would be if the first reaction to the report is negative, this should then exhaust the move down and wash out the sellers. But we’ll see.”**

The chart illustrates this is exactly what happened. The first reaction to the report was very negative and the stock traded down about 10% that day and closed near to the low at 266 SEK. The next day AstraZeneca immediately reversed and started a rapid uptrend. I rang Ingemar and we both laughed at the outcome. And he continued: “**And did you see where it bottomed? At 266 SEK!”**

“Eeeeh... yes...?” I said
“135 SEK from the top at 401!!! The stock trended down 135 SEK in 90 days. Time and price was in harmony! Magnificent!”

Astra Zeneca then rose rapidly for 30 days (figure 13), to a temporary top on the 24th of March before correcting to continue up to another temporary top on the 25th of April. This was the first day the markets were open again after Easter and 60 days from the February low. But it gets even better.

Figure 13

![Figure 13](image1)

Figure 14

![Figure 14](image2)

Note where AstraZeneca topped in April: At 401 SEK, the same level as the top in November the year before. What does this mean? That it rose 401-266 SEK = 135 SEK in 60 days this time. Price and time in harmony again! And if we look even closer, the top in March was at 386 SEK which means that the stock rose 120 SEK in the first 30 days of this uptrend. How much did it then reverse? From 386 down to 341 = 45 SEK, and from here it then rose 60 SEK up to the top at 401 SEK in April.

When Price and time moved in harmony, Gann referred to this as the “squaring” of price and time. That is taking the analysis further and a subject for another article and beyond this short study.

**Nasdaq-100 in 2010 - 2011**

To update this study in mid June 2011, I also want to add a more recent example from the current markets. The Yearly Cycle has been vibrating in many markets this year and to illustrate this, we will look at the Nasdaq-100 index, where it is currently clearly identified.

During the spring and summer of 2010 the Nasdaq-100 fell to a significant low on the 1st of July. In figure 14 we see that the count starts from this low, and how the Yearly cycle has been present. In figure 15 I have zoomed in the latest months and started the count from the low on the 16th of November. Going forward it will be very interesting to see how and if this cycle continuous to vibrate as distinctly as before. Coming up next is the anniversary of the low from summer of 2010; so now I am monitoring how this index moves into the time window around the 1st of July 2011.

Figure 15

![Figure 15](image3)

**More on Gann**

I have been studying and working with Gann Analysis for over a decade and each year and with this, I have gained additional crucial insight and understanding of time and price. For those interested in more background, inspiration and understanding of Gann’s work Bill McLaren’s work, which has been of great help to me, and can be found on his web site, www.mclarenreport.net.au.

Additionally, for any student who wants to go deeper in to Gann’s work, I must recommend David Keller’s edited book *Breakthroughs in Technical Analysis — New Thinking from the World’s Top Minds*. In this book you will find chapter five, by Constance Brown and titled Price and Time. Brown makes an insightful presentation of Gann’s work and the man himself.

**Bibliography**


**Charts and Data**

Trading Session 2
Abstract
The well-known Moving Averages (MA), namely the Simple Moving Average (SMA), the Exponential Moving Average (EMA) and the Weighted Moving Average (WMA), are modified in this paper with the help of the Nyquist Criterion. These modified Moving Averages 3.0 show good smoothing characteristics, illustrate relevant trends and trend reversals in price series without a time lag as far as calculated. With regard to smoothing, trend patterns and time lag bring about a significant improvement on conventional SMA (Moving Averages 1.0: SMA, EMA and WMA). In addition to this, the efficiency of the Moving Averages 3.0 is demonstrated by applying several tests and a simple trading system.

Introduction
In Technical Analysis: SMA are the most widely used indicators. Applied to a price series, the market situation described as a fluctuating price pattern is then smoothed as the chaotic price fluctuations are smoothed out. Smoothing is the most valued advantage of a Moving Average (MA). The fluctuations of price movements are replicated in smoother and clearer patterns. Yet smoothing cannot avoid the main drawback of SMA: a time lag between the pattern of the price series and a MA itself. This can clearly be seen if you consider trend reversals. The reversal of a MA lags behind that of the price series.

The lags for the different SMA with a cycle period n are calculated as follows [1]:

\[ \text{SMA: lag} = \frac{n - 1}{2}, \]
\[ \text{EMA: lag} = 1 \times a -1, \text{for } a = 2/(n+1), \]
\[ \text{WMA: lag} = \frac{n - 1}{3}. \]

It is noticeable that the WMA shows the smallest lag.

Approaches to reduce time lag
In 1994, Patrick Mulloy made an innovative approach to reduce the lag [2]. According to the following expression:

\[ \text{MA: lag} = \frac{n - 1}{2}, \]
\[ \text{EMA: lag} = 1 \times D - 1, \text{for } a = 2/(n+1), \]
\[ \text{WMA: lag} = \frac{n - 1}{3}. \]

It is noticeable that the WMA shows the smallest lag.
TEMA = 3*EMA – 3*EMA[EMA] + EMA[EMA(EMA)]

He applied a EMA once and twice to itself and combined the results with the original EMA.

In 2001, John F. Ehlers made a more general attempt for a MA with reduced lag [3]. It runs:

MMA = 2 * MA[price | cycle period n] - MA[MA | cycle period n].

Ehlers used a MA (SMA, EMA or WMA) and applied this MA a second time to itself. This result MA[MA] is subtracted from the MA modified in this way (notation MMA) is compared with the TEMA in figure 1 (price series S&P 500; as MA and EMA is used with a 50 days period; Ehlers’ MEMA: red line; TEMA: blue line). Ehlers’ simpler relation shows almost the same result as the TEMA as far as the trend reversals are concerned. Both MAs are comparable as to their smoothing behavior. In both MAs – MEMA and TEMA – there is a clear improvement concerning lag compared to EMA (black line).

In the two approaches a MA is applied to a price series and to itself. If one considers the price series and the MA in a general way as a time-dependent time series, the application of a MA to a MA as a sampling procedure and takes findings from the field of signal processing, it can be deduced that the application of a MA to itself (as to MMA and TEMA, see above) is at best only approximately correct. This can be substantially improved by the Nyquist Criterion.

Nyquist Criterion

In signal processing theory, the application of a MA to itself can be seen as a Sampling procedure. The sampled signal is the MA (referred to as MA₁) and the sampling signal is the MA as well (referred to as MA₂). If additional periodic cycles which are not included in the price series are to be avoided sampling must obey the Nyquist Criterion [1, 4].

With the cycle period as parameter, the usual one in Technical Analysis, the Nyquist Criterion reads as follows:

\[ n_1 = \lambda n_2, \quad \text{with} \quad \lambda \geq 2. \]

\( n_1 \) is the cycle period of the sampled signal to which a sampling signal with cycle period \( n_2 \) is applied. \( n_1 \) must at least be twice as large as \( n_2 \). In Mulloy’s and Ehlers’ approaches (referred to as Moving Averages 2.0) both cycle periods are equal.

Moving Averages 3.0

Using the Nyquist Criterion there is a relation by which the application of a MA to itself can be described more precisely. In figure 2 a price series C (black line), one MA (MA₁, red line) with lag \( L_1 \) to the price series and another MA with lag \( L_2 \) to MA₁ (MA₂, blue line) are illustrated. Based on the approximation and the relations described in figure 2 the following equation holds:

\[ \frac{D_1}{D_2} = \frac{(C - MA_1)/(MA_1 - MA_2)}{L_1/L_2} \]

Then follows: \( D_1/L_1 = D_2/L_2 \), with \( D_1 = K - MA_1 \) and \( D_2 = MA_1 - MA_2 \).

According to the lag formulas in the introduction \( L_1/L_2 \) can be written as follows:

Figure 2
\[ \alpha := \frac{L_1}{L_2} = \frac{(n_1 - 1)}{(n_2 - 1)}. \]

In this expression denominator 2 for the SMA and EMA as well as denominator 3 for the WMA are missing, \( \alpha \) is therefore valid for all three MAs. Using the Nyquist Criterion one gets for \( \alpha \) the following result:

\[ (2) \quad \alpha = \lambda \times \frac{(n_1 - 1)}{(n_1 - \lambda)}. \]

\( \alpha \) put in (1) and C replaced by the approximation term NMA, the notation for the new MA, one gets:

\[ \text{NMA} = (1 + \alpha) \text{MA}_1 - \alpha \text{MA}_2. \]

In detail, equation (2) reads as follows:

\[ (3) \quad \text{NMA}[\text{price/ } n_1, n_2] = (1 + \alpha) \text{MA}_1[\text{price/ } n_1] - \alpha \text{MA}_2[\text{MA}_1/ n_2]. \]

\[ (4) \quad \alpha = \lambda \times \frac{(n_1 - 1)}{(n_1 - \lambda)}, \text{ with } \lambda \geq 2. \]

(3) and (4) are equations for a group of MAs (notation: Moving Averages 3.0). They are independent of the choice of an MA. As the WMA shows the smallest lag (see introduction), it should generally be the first choice for the NMA.

\( n_1 = n_2 \) results in the value 1 for \( \alpha \) and \( \lambda \), respectively. Then equation (3) passes into Ehlers’ formula. Thus Ehlers’ formula is included in the NMA formula as limiting value. It follows from a short calculation that the lag for NMA results in a theoretical value zero.

**Test of NMA**

In figure 3 a New Weighted Moving Average (NWMA) (a WMA is used for the MA) is compared with Ehlers’ MWMA. In both cases a WMA with the cycle periods 21 and 200 days, respectively was chosen. In addition, a short period is necessary for the NWMA: 5 days (\( \lambda = 2 \), 21-day NWMA) and 50 days (\( \lambda = 4 \), 200-day NWMA). The German index DAX stands for the price series as an example.

From figure 3 you will see:

- The NWMA is significantly closer to the price series than the MWMA.
- The long-term trend of the 200-day NWMA is precise and close to the price series.
- The distinct trend reversals of the 21-day NWMA are described much more precisely than by the MWMA, and the lag of the NWMA against the price series comes to less than two days.
- In case of 21-day cycle period the NWMA shows a lag which is 3 days shorter than that of the MWMA (compare the two colored arrows).

In summary, it can be concluded that the Moving Averages 3.0 on the basis of the Nyquist Criterion bring about a significant improvement compared with the Moving Averages 2.0 and 1.0. Additionally, the efficiency of the Moving Averages 3.0 can be proven in the result of a trading system with NWMA as basis.

**Trading system based on NWMA**

The trading system consists of one technical indicator, but
The indicator is the Aroon-Oscillator (AO), which is defined as the difference between the Aroon up and Aroon down. The AO is not applied to a price series but to a NWMA applied to the price series: NWMA [price series | n₁, n₂]. Cycle periods for the NWMA are n₁ = 89 days and n₂ = 21 days (\(\lambda = 4.2\)). Cycle period for the AO is 5 days: AO [NWMA | 5]. An Inverse Fisher Transformation (IFT) is applied to the AO: IFT [AO]. The IFT digitizes the AO without lag. Settings: Buy IFT > 0, sell IFT < 0.

In figure 4 you can recognize the trading system: in the upper, red field the digitized AO, and in the lower part of the chart the price series represented by Heikin-Ashi-Candlesticks and the Bollinger Bands. The purpose of the Heikin-Ashi-Candlesticks and the Bollinger Bands is to visually monitor trends and volatility. Long-trades are indicated by the green horizontal bars in the lower part of the chart. For examples, three trades are marked by green (enter) and red (exit) vertical lines.

Furthermore, the trading system described was compared with systems which use other MAs instead of the NWMA [price series | 89, 21] (see above). The following modifications were tested for comparison (no changes due to settings):

- NWMA [price series | 100, 25],
- MWMA [price series | 89],
- WMA [price series | 89],
- SMA [price series | 89].

The first modification is meant to be a stability test for the NWMA [price series | 89, 21] system and the further modifications should be compared with Ehlers’ approach and the standard moving averages WMA and SMA.

The trading system described was tested with 104 selected shares (Europe, USA and Asia, and 18 different sectors according to DJ Sector Titans) and submitted to a backtesting (Software: Investox, Version 5.9.4). The following data were chosen:

- Covered period: January 03, 2000 - January 31, 2011,
- Seed capital/share: EUR 1 000.-,
- Enter-expenses 0.3 % per trade as well as for exit-expenses and slippage.

After each trade closed, all capital available was reinvested. The results of average values per share are presented in tabular form (see Table 1):

- The NWMA trading system shows the highest net profit.
- Compared with a buy-and-hold-strategy the NWMA trading system described is significantly more profitable over others.
- The drawdown numbers of the different trading systems differ only slightly, with the exception of the SMA-system.
- Due to the net profit the NWMA trading system has the best drawdown.
- The largest profit together with the highest number of
profitable trades of the NWMA trading system can be explained by its quick reaction and the minimal lag of the NWMA.

**Conclusion**

The group of Moving Averages 3.0 is a significant improvement over conventional Moving Averages 1.0 (SMA, EMA and WMA) and the well-known approaches to reduce time lags (Moving Averages 2.0). The NMA is suitable for intraday trading as well. A system with a Stochastic-RSI-Indicator (cycle periods 3 and 5) applied to a NWMA (cycle periods 8 and 3), time base 15 minutes, shows profitable trades, too (see figure 5 with two trades as an example).

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**References**


**Charts**

Investox; knöpfel Software GmbH

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**Table 1**

<table>
<thead>
<tr>
<th>Average values/Share</th>
<th>NMAW(89/21)</th>
<th>NMAW(100/25)</th>
<th>MMAW(89)</th>
<th>MAW(89)</th>
<th>MAS(89)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Trades</td>
<td>69,3</td>
<td>62,7</td>
<td>33,2</td>
<td>24,8</td>
<td>20,2</td>
</tr>
<tr>
<td>Trades/y</td>
<td>7,4</td>
<td>6,7</td>
<td>3,6</td>
<td>2,6</td>
<td>2,2</td>
</tr>
<tr>
<td>Net-Profit (EUR)</td>
<td>EUR 46 974,57</td>
<td>EUR 32 292,98</td>
<td>EUR 12 317,75</td>
<td>EUR 8 392,35</td>
<td>EUR 4 552,98</td>
</tr>
<tr>
<td>Buy/Hold-Profit (EUR)</td>
<td>EUR 1 103,09</td>
<td>EUR 1 103,09</td>
<td>EUR 1 103,09</td>
<td>EUR 1 103,09</td>
<td>EUR 1 103,09</td>
</tr>
<tr>
<td>Profitable Trades (%)</td>
<td>61,24%</td>
<td>60,68%</td>
<td>60,09%</td>
<td>61,39%</td>
<td>58,77%</td>
</tr>
<tr>
<td>Max. Drawdown (%)</td>
<td>-8,05%</td>
<td>-7,94%</td>
<td>-9,43%</td>
<td>-7,70%</td>
<td>-14,72%</td>
</tr>
</tbody>
</table>
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- It should add to the body of knowledge in the discipline of international technical analysis

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Applying Trading Strategies to Price Channel Breakout Trading—Statistical Significance of Channel Breakout Variation
by Robin Boldt, MFTA

Abstract
Chart patterns are an important aid in technical analysis, but only when they give high probability outcomes. Hence the key feature of any chart pattern should be reliability. The price channel by Richard Donchian can be classified as one pattern that is said to be reliable. It is a common breakout system as new highs and lows are a readily available piece of information for every financial market participant, especially technical analysts and traders. The purpose of this paper is to test the profitability of price channel variations and to investigate what different outcomes in profitability are resulting from. The key question is: When are breakouts in the Donchian system to be bought and which additional parameters influence its profitability? Research has put a lot of effort in finding the most profitable price pattern, however little research has been published on the right timing within trend following strategies applied to stocks. While I cannot rule out the possibility that technical analysis complements other profitable market timing techniques or trading rules, I decided to put four hypotheses to the test by running them against a comprehensive database of German stocks. Realistic transaction cost estimates were applied. This paper illustrates results testing different parameters on price channel breakouts. The empirical results strongly suggest that easy to use trading parameters and rules can increase profitability.

Part one: Introduction

1.1 Presenting the Hypotheses
Price pattern breakouts are one of the most common forms of breakouts as they are based on pure price action. Donchian breakout signals are generated whenever the market price is equal to or greater than the highest high or the lowest low of the past n periods. There are many types of breakout patterns, such as triangles, channels, wedges, pennants and flags. This work, however, will focus on only the Donchian breakout signals. Numerous empirical studies have proven the general profitability of price channel breakout strategies but there is a necessity to further broaden the research spectrum on this topic. The focus of research has been skewed to the futures market including forex and commodities, and one geographic region: North America. In addition, performance assessments were concerned to find the most profitable periods—understood as days used to plot the upper and lower bands—instead of setting different timing parameters in direct contrast, i.e. price channel breakout strategies based on closing prices, versus price channel breakout signals based on intra-period lows/highs in comparison to various risk and performance metrics. For example, Chande’s price channel breakout test is based on closing prices. It might seem to be just a minor detail and overlooked easily, but from a trading perspective it is a very different approach to wait for closing prices as a breakout confirmation. Odds could favor a valid breakout if the closing price is above the previous n-period high (low), but in reality once the price moves away from the pattern, the trader might be late buying into the breakout as the risk reward ratio starts to narrow, as compared to buying directly into the breakout to benefit from the forming trend. In addition—and at the risk of a pedantic view the practicability of the buy (sell) on the close is a critical consideration as the trader does not know in advance if the closing price will really describe a new n-period high or low. This problem emerges especially when trading European stocks as their closing price is determined by a closing auction, hence their closing price can differ materially from any preclosing indication and still may not make it to a new high or low. For this reason, buy and sell signals on closing prices within this paper are based on buy (sell) on open of next bar if the previous bar describes a completed n-period high (low). Finally, I examined short selling signals based on price channel breakouts (breakdowns) in equal measure using the lower price channel bands as a stop level with momentum strategies.

Despite positive evidence in literature about profitability, the purpose of this paper is to test if other easy-to-use-trading variations and rules actually do add value, which will hopefully lead to practical methods to identify and trade successful breakouts.

The following chart (Figure 1) is a perfect example of a Donchian price channel breakout where Novartis breaks above its 10-day price channel (breakout #1) on an intraperiod (intraday) and closing price. Breakout #2 is slightly different as the stock recovered shortly after the breakout and completed a strong intraday reversal on its closing. Let us assume here that the trader bought into the stock on the back of breakout #1 as per the closing or opening of next bar. When should he close his position? Apparently as soon as the next breakout to the downside occurs negating the initial buy signal. His performance will differ substantially depending on what his exit strategy, e.g. on intra-period price channel breakouts (breakout #2) or price channel breakouts with a closing price confirmation (breakout #3). The same applies for his entry strategy: Apparently, buying directly into the breakout as it happens versus not buying on the closing or opening of next bar at provides a much better entry as a tighter stop can be placed as opposed to a delayed entry—where the breakout is only bought after a closing price, outside the price channel. Executing a trade on breakouts are a zone of conflict and timing.

Before reviewing the analysis, I want to emphasize what this work is and is not: This work does not claim to cut the Gordian
knot to find the most profitable price channel, but intends to emphasize and demonstrate that a successful trading strategy is not built upon a single, but many factors; and that by changing the model’s parameters its profitability can be increased significantly.

To give a new light to the issue, this paper will test the effectiveness of the following four hypotheses, which should lead to practical and working answers on how to identify successful breakouts:

1. Price channel breakout buy and sell signals based on closing prices of completed trading periods are (significantly) less profitable than buying or selling intraperiod highs or lows directly.

2. Price channel breakout sell signals are as profitable as buy signals.

3. The smaller the number of periods charting a n-period high or low around the price line, the more profitable price channel breakout signals are.

4. Price channel breakouts that occur on low volume cannot be considered unreliable.

1.2 Price Channel Breakouts

The price channel, or Donchian channel, is a volatility indicator, calculating the recent price range using the most recent high and low to mark the high and low bands (creating a channel containing the prices). The Donchian channel therefore has a similar chart appearance to other volatility indicators such as Bollinger Bands. For example, a 10-day price channel will chart the level of the highest high in the last 10 days above the price line, and will chart the level of the lowest low in the last 10 days below the price line. Thus, price channels use maximum and minimum price values and not moving averages or standard deviations as boundaries. If the most recent price is a new n-period high (low), it will be charted outside of the price channel and typically generates a buy (sell) signal at the point of the breakout (a price channel breakout). The price channel is a trend following breakout system: Buy when price moves above the channel, sell when the price moves below the channel.

1.3 Related Work and Similar Concepts

"Buy strong action, sell weak one." The use of price channels on charts to generate buy and sell signals is anything but new. Richard Donchian developed the Donchian 4 Week Breakout Channel strategy in the 1960s whereby signals are generated whenever the price exceeds the highs of the four preceding calendar weeks. Like all other trend followers, Donchian emphasized the importance of the price: He does not predict price movements; he just follows them as "trends persist." John J. Murphy and other technical analysts made adjustments to the four week rule, for example by shortening and lengthening the time periods for sensitivity. The chart below is a good example of a price channel breakout on a longer time horizon in which we see the S&P 500 Index breaking above its four month price channel in early 1995 to give a buy signal, which remained intact for years. The basic idea of the trading system is continuous in nature, which means that the trader always has a position, either long or short, rendering it
vulnerable to whipsaws during trendless markets. Richard Dennis was one who attempted to break this continuum, as his famous turtle trading rules are based on buy (sell) signals generated on breakouts above (below) the high (low) of the last 20 bars while using an exit depending on the highest high (for shorts) and lowest low (for longs) of the last ten bars. Tushar Chande tested how the originally continuous price channel breakout system performs if modified to a noncontinuous system by examining the effect of adding a trailing stop (exit on the highest high or lowest low of the last five days) while also modifying the entry rule: “If today’s close is higher (lower) than the highest high (low) of the last 20 days, then buy (sell) on the close and exit the long trade at the lowest low of the last five days on a stop”. This modification naturally increases the quantity of trades and as a consequence results into higher trading costs, making the strategy vulnerable to whipsaws. Overall, his tests showed profitable trading results with 36% winning trades on average and a win/loss ratio of 2.01. Additional empirical studies proved the profitability of the price channel breakout, such as Lukac et. al (1990).

Part Two: Test-Design

2.1 Overview

To recall, the following hypotheses are to be tested:

1. Price channel breakout buy and sell signals based on closing prices of completed trading periods are (significantly) less profitable than buying or selling intraperiod highs or lows directly.
2. Price channel breakout sell signals are as profitable as buy signals.
3. The smaller the number of periods charting a n-period high or low around the price line, the more profitable price channel breakout signals are.
4. Price channel breakouts that occur on low volume cannot be considered unreliable.

In a first run, a testing of hypotheses 1 and 2 will be conducted (Test #1) where the same breakout system is run on two different entry signals (all other things being equal) using a ten day period to calculate the price line. The testing will help to emphasize the importance of the right timing strategy in place as many trading strategies are (wrongfully) deemed to be not profitable without looking at those two parameters. In addition, the performance of long and short signals is compared.

Hypotheses 3 will be tested through Test #2 using the most profitable trading setup emerging from Test #1.

The purpose of Test #3 is to assess the importance of volume during price channel breakouts, by filtering out breakouts that occur on low volume. The question here is: Are price channel breakouts that occur on low volume significantly less profitable?

Table 1: Test #1 – Paired t-test results

<table>
<thead>
<tr>
<th>Setup 1</th>
<th>All</th>
<th>Long</th>
<th>Short</th>
<th>Mean Net Profit per Stock</th>
<th>13,865.26</th>
<th>6,029.32</th>
<th>7,835.94</th>
<th>4,179.72</th>
<th>1,462.84</th>
<th>2,716.88</th>
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<tbody>
<tr>
<td>Gross Profit</td>
<td>26,718.92</td>
<td>13,394.28</td>
<td>13,324.64</td>
<td>12,590.22</td>
<td>5,757.35</td>
<td>6,832.87</td>
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<td></td>
</tr>
<tr>
<td>Profit Factor</td>
<td>2.49</td>
<td>2.21</td>
<td>3.33</td>
<td>2.19</td>
<td>2.23</td>
<td>4.53</td>
<td></td>
<td></td>
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<tr>
<td>Total Number of Trades</td>
<td>202</td>
<td>105.50</td>
<td>96.77</td>
<td>81.70</td>
<td>43.43</td>
<td>38.27</td>
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<tr>
<td>Percent Profitable</td>
<td>33%</td>
<td>33%</td>
<td>34%</td>
<td>36%</td>
<td>33%</td>
<td>40%</td>
<td></td>
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<tr>
<td>Average Trade Net Profit</td>
<td>66.45</td>
<td>55.79</td>
<td>78.05</td>
<td>45.68</td>
<td>30.96</td>
<td>68.17</td>
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<tr>
<td>Average Winning Trade</td>
<td>381.50</td>
<td>373.99</td>
<td>389.52</td>
<td>412.13</td>
<td>390.67</td>
<td>430.03</td>
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<tr>
<td>Average Losing Trade</td>
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<td>-100.58</td>
<td>-82.69</td>
<td>-153.64</td>
<td>-141.62</td>
<td>-166.05</td>
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<tr>
<td>Ratio Avg.Win./Avg.Los.</td>
<td>4.74</td>
<td>4.26</td>
<td>7.14</td>
<td>3.50</td>
<td>3.98</td>
<td>5.56</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Largest Winning Trade</td>
<td>1,025.69</td>
<td>810.08</td>
<td>934.77</td>
<td>1,017.98</td>
<td>676.03</td>
<td>937.95</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Largest Losing Trade</td>
<td>-2,128.72</td>
<td>-2,045.11</td>
<td>-1,612.51</td>
<td>-2,006.86</td>
<td>-1,787.95</td>
<td>-1,702.40</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Commission</td>
<td>10,562.28</td>
<td>5,865.82</td>
<td>4,696.46</td>
<td>3,885.28</td>
<td>2,199.58</td>
<td>1,685.69</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max. Drawdown</td>
<td>-3,343.72</td>
<td>-2,717.74</td>
<td>-2,164.90</td>
<td>-3,609.01</td>
<td>-2,692.74</td>
<td>-2,415.83</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max. Intraday Drawdown</td>
<td>-3,920</td>
<td>-3,237.37</td>
<td>-2,702.32</td>
<td>-4,241.17</td>
<td>-3,431.82</td>
<td>-2,949.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Positions</td>
<td>209.1</td>
<td>6,029.32</td>
<td>7,835.94</td>
<td>84.80</td>
<td>45.03</td>
<td>39.77</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Position Changes</td>
<td>418.2</td>
<td>13,394.28</td>
<td>13,324.64</td>
<td>169.60</td>
<td>90.07</td>
<td>79.53</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
price for sells respectively. Of course, the bid and ask price is an estimation of a realistic execution price.

2.4 Money Management

Each trading portfolio per stock is set up with an initial capital of €100,000. The size of an order is not fixed but depends on the risk attached to each buy and sell signal. The risk per trade is defined by the difference between the entry and the stop level. The system does not allow a risk of more than 2% per trade of the current capital.

2.5 Supplementary

Pyramid trading, understood as of using profit generated from an existing position to acquire additional positions, is not incorporated in the empirical testing. Hence, there is no adding to an existing position.

Part Three: Backtesting and Empirical Results

3.1 Test #1

Test #1 aims to test the profitability of price channel breakout trading using two different set-ups:

**Setup 1:** Entry: Buy (sell short) at market if the stock hits a fresh 10-period high (low).

**Setup 2:** Entry: Buy (sell short) on next bar when stock’s close is above its n-period high (low).

All other parameters are held equal: exit long (short) position on stop when stock breaks below the trailing price level of the lower (upper) price channel or when the break-even level is touched. The stop loss is set to breakeven once the open profit exceeds 2€ so that there no longer risk attached to the trade. The exit is defined as follows: Take profits when 20% of the initial risk is earned.

Setup 1 yields on average—as seen in table 2—13,865€ per stock over the three year period, which is significantly higher than in setup 2. Further testing elaborates that this increased profitability is a result of a higher trade frequency (202 vs. 81 trades on average) and also a significantly higher average net profit per trade, which is an important finding.

3.1.1 Supplementary: Test #1.2—Long vs. Short Trades

Additional test results, presented in table 4 and 5, clearly show significant profitable short sells signals based on price channel breakdowns, are and that the signals are not to be neglected:

3.2 Test #2

Hypothesis 2 will be tested through Test #2, using the most profitable trading strategy emerging from Test #1 which is setup 1. For the purposes of this test, the chosen entry method was a 5-, 10- and 20-period high and low on a daily chart (all other parameters hold equal). I intentionally did not include any timeframe optimization to avoid overfitting the data. The aim is to observe a general change in profitability if the number of periods that will chart a n-period high or low around the price line are changed.

**Setup 3:** Buy (sell short) at market if the stock hits a fresh

<table>
<thead>
<tr>
<th>Table 2: Test #1 — Paired t-test comparing the mean net profit per stock</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean performance</strong></td>
</tr>
<tr>
<td>13,865.26</td>
</tr>
<tr>
<td><strong>Mean 1 – Mean 2</strong></td>
</tr>
<tr>
<td><strong>N</strong></td>
</tr>
<tr>
<td><strong>Standard deviation</strong></td>
</tr>
<tr>
<td><strong>Standard error of mean</strong></td>
</tr>
<tr>
<td><strong>df</strong></td>
</tr>
<tr>
<td><strong>p-value</strong></td>
</tr>
<tr>
<td><strong>t</strong></td>
</tr>
<tr>
<td><strong>Statistically significant?</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3: Test #1 — Paired t-test comparing the average net profit per trade</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean performance</strong></td>
</tr>
<tr>
<td>66.45</td>
</tr>
<tr>
<td><strong>Mean 1 – Mean 2</strong></td>
</tr>
<tr>
<td><strong>N</strong></td>
</tr>
<tr>
<td><strong>Standard deviation</strong></td>
</tr>
<tr>
<td><strong>Standard error of mean</strong></td>
</tr>
<tr>
<td><strong>df</strong></td>
</tr>
<tr>
<td><strong>p-value</strong></td>
</tr>
<tr>
<td><strong>t</strong></td>
</tr>
<tr>
<td><strong>Statistically significant?</strong></td>
</tr>
</tbody>
</table>

2.2 Statistical Significance of Channel Breakout Variations

The key question of the upcoming price channel breakout variations is whether the differences in the profitability are statistically significant or not. In this paper, profitability is understood as mean net profit per trading strategy and average net profit per trade. Broadly speaking, a test of significance is a procedure by which sample results are used to verify the truth or falsity of a null hypothesis (H₀). The decision to accept or reject H₀ is made on the basis of the value of the test statistic obtained from the data at hand. I will use a paired t-test in this paper as the measurements are taken from the same stock universe. By using the paired sample t-test, I can statistically conclude whether adjustments to certain price channel trading parameters have improved the profitability or not.

2.3 Data and Transaction Costs

The scope of this test includes stocks that are DAX members as per September 2010. This amounts to 30 securities spanning three years as the performance will be tested on historical data from 1/1/2004 through 12/31/2009. The reason I chose these stocks and that timeframe is twofold: First, to avoid ill-liquid stocks where realistic historical results could not be generated. Second, to assure a test window large enough to generate statistically sound results, including a broad data sample and conditions. Realistic transaction cost estimates were applied in the amount of 0.10% per transaction side. To avoid unrealistic fills, the execution price is conducted at ask price for buys, or bid...
Table 4: Test #1 – Paired t-test comparing the mean net profit per stock

<table>
<thead>
<tr>
<th></th>
<th>Setup 1 Shorts</th>
<th>Setup 1 Longs</th>
<th>Setup 2 Shorts</th>
<th>Setup 2 Longs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean performance</td>
<td>7.835,94</td>
<td>6.029,32</td>
<td>2.716,88</td>
<td>1.462,84</td>
</tr>
<tr>
<td>Mean 1 – Mean 2</td>
<td>1806.6150</td>
<td>1254.0317</td>
<td>638.4028</td>
<td>574.2934</td>
</tr>
<tr>
<td>N</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>4424.5568</td>
<td>4453.8320</td>
<td>3496.6762</td>
<td>3145.5346</td>
</tr>
<tr>
<td>Standard error of mean</td>
<td>807.8099</td>
<td>813.1547</td>
<td>638.4028</td>
<td>574.2934</td>
</tr>
<tr>
<td>df</td>
<td>29</td>
<td>29</td>
<td></td>
<td>29</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0262</td>
<td>0.1048</td>
<td></td>
<td></td>
</tr>
<tr>
<td>t</td>
<td>2.3431</td>
<td>1.6742</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Statistically significant?</td>
<td>Yes</td>
<td>No</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Test #1 – Paired t-test comparing the average net profit per trade

<table>
<thead>
<tr>
<th></th>
<th>Setup 1 Shorts</th>
<th>Setup 1 Longs</th>
<th>Setup 2 Shorts</th>
<th>Setup 2 Longs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean performance</td>
<td>55.79</td>
<td>78.05</td>
<td>30.96</td>
<td>68.17</td>
</tr>
<tr>
<td>Mean 1 – Mean 2</td>
<td>-22.2557</td>
<td>-37.216</td>
<td>-14.9954</td>
<td>94.2504</td>
</tr>
<tr>
<td>N</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>40.3487</td>
<td>42.7422</td>
<td>74.0995</td>
<td>94.2504</td>
</tr>
<tr>
<td>Standard error of mean</td>
<td>7.3666</td>
<td>7.8036</td>
<td>13.5287</td>
<td>17.2077</td>
</tr>
<tr>
<td>df</td>
<td>29</td>
<td>29</td>
<td></td>
<td>29</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0035</td>
<td>0.0644</td>
<td></td>
<td></td>
</tr>
<tr>
<td>t</td>
<td>3.1739</td>
<td>1.9226</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Statistically significant?</td>
<td>Yes</td>
<td>No</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Test #2 – Paired t-test results

<table>
<thead>
<tr>
<th></th>
<th>Setup 3</th>
<th>Setup 4</th>
<th>Setup 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Net Profit per Stock</td>
<td>21,622.76</td>
<td>13,865.26</td>
<td>8,977.34</td>
</tr>
<tr>
<td>Gross Profit</td>
<td>47,876.75</td>
<td>26,718.92</td>
<td>15,245.41</td>
</tr>
<tr>
<td>Profit Factor</td>
<td>2.10</td>
<td>2.49</td>
<td>3.14</td>
</tr>
<tr>
<td>Total Number of Trades</td>
<td>304.80</td>
<td>202</td>
<td>132.03</td>
</tr>
<tr>
<td>Percent Profitable</td>
<td>44%</td>
<td>33%</td>
<td>26%</td>
</tr>
<tr>
<td>Average Trade Net Profit</td>
<td>67.46</td>
<td>66.45</td>
<td>61.27</td>
</tr>
<tr>
<td>Average Winning Trade</td>
<td>341.46</td>
<td>381.50</td>
<td>406.79</td>
</tr>
<tr>
<td>Average Losing Trade</td>
<td>-147.92</td>
<td>-92.10</td>
<td>-62.33</td>
</tr>
<tr>
<td>Ratio Avg.Win./Avg.Los.</td>
<td>2.55</td>
<td>4.74</td>
<td>8.25</td>
</tr>
<tr>
<td>Largest Winning Trade</td>
<td>1,158.80</td>
<td>1,025.69</td>
<td>874.03</td>
</tr>
<tr>
<td>Largest Losing Trade</td>
<td>-2,599.54</td>
<td>-2,128.72</td>
<td>-1,667.40</td>
</tr>
<tr>
<td>Total Commission</td>
<td>23,524.39</td>
<td>10,562.28</td>
<td>4,994.25</td>
</tr>
<tr>
<td>Max. Drawdown</td>
<td>-5,715.01</td>
<td>-3,343.72</td>
<td>-2,343.05</td>
</tr>
<tr>
<td>Max. Intraday Drawdown</td>
<td>-6,227.29</td>
<td>-3,920</td>
<td>-2,892.24</td>
</tr>
<tr>
<td>Total Positions</td>
<td>315.47</td>
<td>209.10</td>
<td>136.90</td>
</tr>
<tr>
<td>Position Changes</td>
<td>630.93</td>
<td>418.20</td>
<td>273.80</td>
</tr>
</tbody>
</table>

5-period high (low).

Setup 4: Buy (sell short) at market if the stock hits a fresh 10-period high (low).

Setup 5: Buy (sell short) at market if the stock hits a fresh 20-period high (low).

3.3 Test #3

The purpose of Test #3 is to assess the importance of volume during price channel breakouts, by filtering breakouts that occur on low volume. The question here is: Should price channel breakouts that occur on low volume be avoided?

Setup 6: Buy (sell short) at market if the stock hits a fresh 5-period high (low).

Setup 6v: Buy (sell short) at market if the stock hits a fresh 5-period high (low) but only when volume exceeds its five day volume exponential moving average (EMA).

Setup 7 and 8 are structured as in Test #2. All things hold equal for Setup7v and Setup8v except for a volume threshold as in Setup 1v, using a 10 and 20 day volume EMA respectively.

The results presented in table 10 and 11 provide much insight: I have always been a fan of breakouts on relatively “decent” or high volume but the test results tell a different story: Price channel breakouts that occur on low volume should not be avoided. Trading price channel breakouts only when they occur on relatively higher volume will have a negative impact on the total profit and loss of this signal, because breakouts that occur on average volume are also reliable.
Discussion and Conclusion

Price channel breakouts, as well as breakdowns, describe zones of conflict or “areas of doubt”.\(^{10}\) Quite often price breakouts turn out to be misleading moves known as whipsaw breakouts. Therefore it is crucial for a trader to assess the probabilities of a valid buy or sell signal whenever planning on opening a new position based on a price channel breakout.

In general, price channel breakouts are profitable, however **Test #1** confirmed hypothesis 1 whereby **price channel breakout buy and sell signals based on closing prices of completed trading periods are significantly less profitable than directly buying or selling intraperiod highs or lows**. Setup 1 (buy at market if the stock hits a fresh 10-period high) offered a higher average profit factor (2.49 vs. 2.19), a significant higher average trade
net profit (66.45€ vs. 49.01€), a better ratio of average win-loss ratio (4.74 vs. 3.50) and a statistically significant mean net profit per stock (13,865.26€ vs. 4,179.72€) compared to setup 2. Setup 1 presented an even more compelling risk profile with a lower maximum drawdown (-3,343.72€ vs. -3,609.01€) and a smaller average losing trade (-92.10€ vs. -153.64€). Setup 1 and 2 are typical trend following setups with 33% and 36% percent profitable trades on average. The empirical findings suggest that there is a payoff to participate in breakouts (sell into breakdowns) at an early stage, if combined with tight stops.

Test #1.2 demonstrated that short sells based on price channel breakouts (breakdowns) are, interestingly, on average more profitable than the buy signals, and to some extent statistically significant more profitable. A reason for that could be attributed to the fact that breakdowns trigger stop-loss orders which then quickly generate selling pressure, whereas decisive moves to the upside most often require actively entered buy orders in reaction to the move, compared to automatically triggered stop orders. This evidence supports the observation that many market participants do not feel comfortable to buy into a new high by chasing the market as they can hardly assess the probabilities of price continuation, whereby stop losses are automatically entered in loss aversion.

Overall, the high frequency of trades suggests that trading costs are a significant factor in overall performance. It is noteworthy, that most of the high frequency trading accounts in Europe do not pay more than 0.02% commission (for risk free trades) in contrast to the 0.10% commission incorporated in the tests within this paper.

Test #2 indicates that the smaller the number of periods charting a n-period high or low around the price line, the more profitable price channel breakout signals are. Profitability, however, is not the only key metric when assessing a trading strategy. Setup 5, using a 20-period, offers a superior profit factor (3.14 vs. 2.10 and 2.49), a smaller average losing trade (-62.33€ vs. -147.92€ and -92.10€) and a lower maximum drawdown (-2892.24€ vs. -5715.01€ and 3343.72€) as well as a smaller trading frequency, which explains the lower mean net profit per stock over the observed trading period. The higher trading frequency in setup 3 may be attractive to traders if their trading costs are low. Again, one of the key questions you must ask when you see system variations is whether the differences fit your trading style. Statistically significant profitability of channel breakout variations cannot be regarded in isolation.

Test #3 successfully overcomes the conventional wisdom that breakouts that occur on low volume can be considered unreliable. With respect to percentage profitable trades or average winning trades, it was not at all statistically significant whether the breakout or breakdown occurred on above average volume or not. Breakouts on above average volume show the same hit ratio but a lower mean net profit, as the volume threshold halves the number of total trades—resulting in lower profitability. In short: On average, a 50% lower trade frequency yields a lower mean net profit (ceteris paribus) while both setups offer the same mean net profit per trade.

To summarize, the empirical results strongly suggest
that trend following on stocks offer a positive mathematical expectancy (in line with previous research) and that correctly timed entries and exits—although often underestimated—significantly influence the profitability of a price channel breakout.

Future research in that regard is requested to expand testing on other stocks, timeframes and entry and exit rules.

Bibliography
3. Dixon, Barbara Saslaw (1978) "Donchian’s 20 guides to trading commodities" Commodity Research

References
iii. Barbara Saslaw Dixon (1978) "Donchian’s 20 guides to trading commodities" Commodity Research, p.1

Software and Data
Tradsesignal Standard Edition, Version 5.6.5.0, Copyright 1996-2010 tradesignal GmbH
MS Office XP
Data provided by teletrader and Reuters
All programming used to create the trading strategies in the paper was written in the equilla language

Appendix (Endnotes)
5. Murphy (1999), p. 216
Abstract
The t-grid is a series of stacked trend channels with the base channel defined by the first swing of the trend and determines price vibration, support and resistance ranges, allowing the trader to create a trade strategy around the t-grid concept. The t-grid assists in determining if price is relatively high or low by breaking up the major trend into smaller defined ranges. With application of the t-grid, the trader is presented with effective and well-defined trading opportunities.

In this study we step through the process of creating a t-grid from its origin and progress it through its trend development.

Introduction
According to the old adage it is easy to make money trading the markets—buy low and sell high. But the question when is the market low and when is it high is easily answered. It is relatively easy to define the market as low when it is rising off a well-defined base, but further into the trend the question if the market is high or low is problematic at best.

The trend grid, or t-grid, is a concept providing useful insight to answer this question. At the heart of the idea is the understanding that the initial swing of a major trend provides the building block for the entire trend. The rules of the t-grid provides a systematic way of identifying key levels that define shorter trading ranges, periods in which it is possible to label the market as low or high. Simple bar analysis can then be used to identify entry and exit times.

This method favours stocks and commodities that trend well and market-wide instruments like the stock indices and currencies. Large cap stocks also fit the t-grid well, but smaller cap stocks do not as they do not exhibit stable long-term trends relative to large caps. Commodities produce good t-grids on long-term charts but not so well on shorter time frames. Whenever an instrument enters a prolonged trend, it is likely to follow the t-grid structure.

A good example of the t-grid is the Australian Dollar over the past 12 years.

The t-grid Concept and Construction
The t-grid is a series of stacked trend channels with the base channel defined by the first swing of the trend. As the trend unfolds and price moves beyond the base channel, another channel is added on top of the existing channel. Each new channel line acts as an “attractor” and price advances towards it. It will also act as a resistance point. While the trend continues, prices will eventually move through this channel and a new channel will be stacked on the existing channels.

Volatility tends to increase as the trend unfolds, so not all new channels will be of equal importance. Rather than a stacking of channels it is better to view the process as a doubling of the channel width. In Figure 1 the darker, solid lines represent the doubling of the channel. The original channel width maintains some value and is represented by a broken line.

Just as price is defined by the original swing, so is time. The vertical lines in Figure 1 are spaced at the time length between the first two lows. This time length—let’s call it a vibration—becomes the basic unit of time for the trend and significant turning points will tend to line up with these vibrations.

This combination of time and price structured by the initial swing of the trend provides a powerful method to break up the evolving trend and identify key levels and events on which to take action. Simple bar analysis will identify price and time levels to open and close trades.

In this study we will step through the process of setting up a t-grid from its origin and progress it through its trend development. We will first focus just on the price component.

Drawing the first channel of the t-grid

A channel can be first drawn with the base trendline between a low (high) and its retest and the guideline drawn through the intervening high (low). This simple definition
will result in a channel being drawn when there are no firm signs of a reversal of the previous trend and the action is considered a pullback rather than the start of a new trend. In such circumstances it is better to wait for a stronger sign of a reversal before starting the t-grid. When the t-grid is drawn it is done so from the origin of the trend. Figure 2 shows the Australian Dollar starting its t-grid in this fashion.

The low point was made in April 2001 and retested in September. The intervening high of August was first breached in April 2002 providing the first opportunity to draw the channel. However, it was not until June 2002 that the last swing high of the downward trend was breached, giving us a firmer indication that a trend reversal may be developing. This was the time to draw the t-grid.

The t-grid merely indicates key support and resistance levels for the new uptrend. These are points at which we can rate the market as relatively high and low. In Figure 2 the Australian Dollar has moved into the higher channel so the first lower channel line is support—or the market at a low—and the higher channel line is resistance—or the market at a high. How meaningful this is depends on the width of the immediate channel in relation to average daily range—the larger the ratio, the greater the potential opportunity to profit from a trade within the immediate channel.

We must remember, and within this concept, is that channel lines act as key psychological points in the market just as swing highs and swing lows. The channel lines relate price to time—key points are not just determined by price, but also have a time dimension. These lines will gain in importance each time price changes its behaviour as it approaches these levels. The more often price responds to channel lines in the t-grid, the more significant the t-grid becomes. This responding to the channel lines develops and supports the notion of the market being high (and attracting sellers) or low (and attracting buyers). When a channel breaks then the channel lines reverse their roles—resistances become support and supports become resistance.

**Progressing the t-grid**

As a trend unfolds it will move through a series of channels. In Figure 2 the Australian Dollar has broken a channel resistance, suitably accompanied by a wider daily range, and sets up the opportunity to test the next channel line. On this occasion the rally stopped in the middle of the new channel and the last bar made a bearish closing price reversal. That bar suggests downside action for the next bar. At this point the t-grid has not been confirmed, so we await the outcome of the drop back to the lower channel. Figure 3 shows the next couple of bars falling back into the lower channel.

The concept of resistance becoming support did not hold in the strict meaning of this idea, and price returned into the lower channel. However, and of note, the downward momentum was not sustained as with the last bar prices moved up, producing a bullish closing price reversal, a signal for higher levels to come. The channel lines should be treated as a guide with the final confirmation coming from price action. We now need prices to follow-through on the upside and move back into the higher channel.

**Figure 3:** retest of a previous channel resistance.

**Figure 4:** the rally progresses.

**Classic t-grid action**

The next swing shown in Figure 4 demonstrates the classic within the t-grid.

First, the bullish closing price reversal day respected the resistance of the channel line. The next bar responded with a drop, but the narrowing and small range warned that the drop was of a minor corrective nature. The following three bars provide the break of the channel line and its retest, suggesting that the psychology of the market was turning bullish. The subsequent bar with an expanding range confirmed the market was at the lower end of the range and that a rise to the higher end of the range likely which occurred in the next two bars. Generally, once a channel resistance has been tested we would expect a drop back to channel support. The last bar of Figure 4 is we see price action respects the resistance, but provides no clear indication of direction. It will be the next bar that would confirm the direction.

Figure 5 shows the outcome:

The following price bar pushed through the channel resistance and closed at the high and above the previous bar’s high, providing a strong signal that the attempt to react to channel resistance had failed and that once again the market is in a ‘low’ position. The next objective is the done by doubling of the channel; and as seen, the next solid line in Figure 5, which was achieved several months later. In this case, the market did pause at the halfway point in the channel—the level of the third channel in the sequence. Note how a closing price reversal signaled further downside. A contracting range provided some
warning that the downside may not continue, but it was the following month with its bullish expanding range that signalled prices were ready to resume their ascent.

Figure 5: Another channel resistance breaks.

The next channel resistance did not contain the rally and price continued to the next minor channel resistance. On this occasion there was no weakening of the uptrend as price approached the channel resistance. There was no clear bar signal for the top. Such action is a subtle sign that the market remains in a strong underlying upward trend.

The drop off the high did respect the support of the channel line, albeit for just the one bar, and at the time would have generated expectations of the rally resuming. That expectation was squashed on the next bar as prices quickly gave way to a drop below the supporting channel line. The decline extended only to the next minor channel line, which coincides with the level of support where the rally paused several months earlier.

The rest of Figure 5 shows price contained within the immediate minor channel just below the major channel resistance. With the last bar the t-grid is neutral on trend direction. We can have a bias for the upside as price rose easily through the main channel resistance on its way to its recent high, and since then has been responding to the upward sloping t-grid. However, the inability to hold above the main channel resistance highlights current weakness in the trend. The t-grid identifies the minor channel resistance that contained the recent high as the level to break to clear the way for further gains. A drop through the nearby minor channel support—that contained the recent decline and marked a pause to the earlier rally—will project prices back to the last major channel line around 0.6300.

The t-grid is not a forecasting tool, although it has forecasting implications; and merely highlights the key levels in the market.

Figure 6: Failure to resume the rally.

Trading the t-grid

By identifying key support and resistance levels within a trend, the t-grid defines the market in temporary high or low states that provide the opportunity for initiating trades and closing them out. But to take action when confirmations are provided by the market means that not all channels will be tradeable. Particularly in the early stages of the trend when then the range is narrow, the signals generated to buy and sell do not offer a sufficient range to return a profit. As the trend unfolds and the market trades over more than one base channel widths (as seen in the previous figures) will there be an opportunity to profit from following the structure of the t-grid? To answer this, an easy measure to make is the ratio of the channel width to the average daily trading range: the higher the ratio the greater the possible opportunity for a profitable return. Where the ratio is small then the opportunity for profit may be too small to justify the risk on the trade.

One way around the problem is to redraw the t-grid on a smaller time frame and follow signals generated there against the main channel lines to initiate and exit trades. As the trend evolves the channels become wider so in time the problem of the ratio diminishes.

The Time Dimension

Just as key price levels are determined, key time points can also be determined. Figure 7 shows the “vibrations” for the Australian Dollar:

Figure 7: time vibrations of the trend.

The unit of vibration is the time between the two lows that set up the t-grid. This unit can be projected forward and key price actions should be expected at these time points. Generally the market will maintain a consistent theme over the period
of the vibration—trending up, trending down or ranging. At times a combination will be seen such as trending for most of the vibration period but making a pullback into the end of the period. You should allow a “window” for the turn, generally one or two bars before and after the identified or projected date.

Time is secondary to price and helps in understanding the ebb and flow of the evolving trend. The time vibration is the additional information need to understand the position of the market. It is particularly useful when price does not provide decisive signals.

In Figure 7 we can see that the last high occurred within the window for the end of the vibration period. Nevertheless with the next bar, on the date for the vibration rollover, the drop was arrested. The firm drop on the last bar confirms that a period high is in place. Reviewing the last 2 vibration periods we can see that price rallied during the first and built the top in the second. Now with a high confirmed the expected outcome is a decline in the next vibration cycle, to break the nearby channel line and eventually test the minor channel line that contained and supported the last sell-off. Figure 8 shows the outcome.

**Figure 8: Outcome from the 2004 high**

The Australian Dollar took 2½ vibration periods to test the minor channel line and along the way price responded around the immediate channel line. This action is a warning that price outcomes are likely to vary from the expectations implied by the t-grid. The action off the low eventually moved back above the major channel line. Note how the market topped at the end of the last vibration period, attempted a reversal that did not break the immediate channel support. With the last bar now closing at the high of the bar, the Australian Dollar appears ready to rally again.

**Back to the present**

Let’s return to the Australian Dollar and see the result to the present time (May 2011):

We can see that throughout 2007 and into 2008 the Australian Dollar progressed into the next broader channel, reacting around the minor channel lines and peaking with a bearish closing price reversal just before the next major channel resistance. This time the market fell aggressively. The t-grid itself cannot anticipate such a reaction; it can only highlight potential levels of support and resistance and identify the rhythm of the move. Price fell through all but two channel lines, but the time of the decline spanned one vibration cycle. After another vibration cycle of building a base, price rallied again and quickly fell in with the existing t-grid structure. The steep decline does not appear to have altered the t-grid. As a general rule, only when the base trendline of the t-grid is broken can we accept that the t-grid is then invalid and expired.

**Figure 9: Rally from the origin to the present.**

Later in 2010 prices returned to the channel line marking the containment of the 2008 rally. After a vibration period of testing this channel line prices moved above it in April 2011. This creates the opportunity of possible progression to the next major channel line now near 1.5000. However, and as we see, the move through the channel line has not yet been confirmed; prices remain vulnerable to a breakdown of support and a decline. While prices hold above the 1.0380 channel support, a rise through 1.1000 would confirm a new rally. The Australian Dollar will then be ‘low’ again. Only a drop below the 1.0300 channel line tell us the Australian Dollar is vulnerable to a new decline.

**Application**

The t-grid divides the broader trend into smaller well-defined ranges. Such an approach will not suit all types of traders. Long-term traders who prefer a “buy and hold” approach may find that the t-grid detracts from following the underlying trend. However, the t-grid will still be useful as an analytical tool for setting stops, adding to positions and re-entering trades.

The t-grid will best appeal to swing traders looking for opportunities to trade defined ranges, buying once channel supports are confirmed and taking profit on tests of channel resistances, and vice-versa.

Traders can take advantage of redrawing the t-grid on smaller time frames and take action closer to the moment channel lines are confirmed.

**Summary**

The t-grid offers a way to get a handle on whether or not the market is relatively high or low by breaking up the major trend into smaller ranges. It is not a full definition of the trend and the system can expand indefinitely. As the trend progresses volatility increases and the channel is continually doubled to account for that increased volatility. By waiting for price action to confirm the validity of the channel lines the trader is presented with effective and well-defined trading opportunities.
Is Average True Range a Superior Volatility Measure?

by Glenn Marci, CFTe, MFTA

Abstract

This paper considers applicability of different volatility measures such as Average True Range and Standard Deviation. During the recent financial crisis volatility has been difficult to capture for a lot of technical indicators, so the task is to review the results of the two measures during the crisis.

During the course of the paper the question will be addressed whether or not there is a kind of “good” and “bad volatility”. Good volatility would be characterized as volatility generated during a trend phase and it should confirm a trend. Bad volatility would therefore be rapid up and down swings in price movements, where the market does not trend in a specific direction.

Therefore, a special emphasize will be put on crisis times as during the past two years when prices in markets moved rapidly and irrationally with intensive changes of trends. As a simple technical measurement tool, Bollinger Bands will be applied to prices as opposed to a Keltner band system. In addition, a stop-and-reverse system is employed for each of the measures.

1. How Does Volatility Change During Times of Market Crisis?

Markets move in trends. This is one of the most fundamental concepts in technical analysis and the concept is required for acceptance to apply technical analysis. A current market trend is more likely, over time, to continue than to end. As a consequence, the question arises how far a trend will continue and when it is going to end. In order to capture these trends and underlying price movements there needs to be measures which describe the magnitude and speed of a movement. Generally this is done via a concept that is described with the general term volatility. But what measures exist and what are the differences among them?

Benoit Mandelbrot pointed out in his book, “The (mis)Behavior of Markets” that the magnitude of price moves often shows dependence to past moves, but that the direction of moves is not always clear. He speaks of dependence without correlation as a strong fall in prices is more likely to be followed by yet another strong move, but the direction of the subsequent move may be uncorrelated to the past. Is there a possibility for a volatility measure to capture this kind of relationship?

The first part of this study will answer the first question and review the basics of measuring price moves. To do this, a theoretical fundament is laid of the different possibilities of measuring volatility. Several volatility measures will be briefly touched, but the focus will be put on the concepts of standard deviation (SD) and average true range (ATR), together with their applications in technical indicators called Bollinger Bands and Keltner Bands.

To answer the second question, both concepts of volatility are scrutinized on a theoretical level before they are applied to real markets. Differences of the measures are presented as well as statistical analysis of real world data to make the measures comparable. For each of the measures a band system will be tested as well as a stop-and-reverse (SAR) system. Results will be presented for different markets and market phases and the change of volatility will be analyzed. In particular the impact of the financial crisis on the markets and the impact on trading models will be evaluated.

2. Theoretical Background

a) What is volatility?

Volatility is a measure of a market’s variability. It could also be called a measure of a market’s activity. There are very many ways to measure how dispersed prices on a market are, and each focuses on a specific aspect of a movement or price range. Volatility always depends on the time horizon on which it is calibrated, but while some measures change dramatically with time, others will only show moderate changes. Some measures include all data points within the look back period; some only use the extreme values during the time. However, all volatility measures try to summarize the movement of a market or security over a specified time in one figure.

Discernment has already been made between different kinds of volatility. Is there good or bad volatility? Most technical indicators need a certain degree of price movement to reach a meaningful level for which the indicator has a force of expression. And most indicators try to give an indication of the likelihood of prices in a specified direction. Either they are confirming the direction of prices or trends as with using moving averages or they are indicating that a reversal of the current price action is likely. An example of the latter type of indicators would be the class of oscillators, which try to find areas of overbought and oversold prices.

Here the focus is on volatility, generated during a trend phase. It thus fits into the first category of indicators to be confirming price action. As a consequence, volatility is “good” if it rises due to price moves in one direction or due to an acceleration of an ongoing price move, which is another description of a trend. “Bad” volatility is then characterized as volatility of prices which are fluctuating without trend direction. This definition is close to the one given by Thomas Stridsman in his book “Trading Systems That Work”. He called volatility which increases with the direction of a trend “good” as it works in favour of positions from trend following systems and everything that works against the positions from such a system “bad”.


Measures of volatility range from maximum-minimum comparisons, dispersion around a trend line, historical volatility or implied volatility as derived by options pricing to measure expected volatility in the future. Perry J. Kaufman suggests four measures of volatility which show the expansion and contraction of volatility over time, which would be a desirable feature in the analysis. 

Besides price change over a defined time, maximum price fluctuation and the sum of absolute changes, Kaufman favoured the ATR as it is also suitable to give an impression of future volatility. Thus, this measure has already proven to have advantageous characteristics, so it will be the first candidate of volatility to be reviewed.

When John Bollinger was searching for a volatility measure to construct trading bands he favoured seven different volatility measures and finally decided to use Standard Deviation (SD).

In his view the special quality of this measure of volatility was to magnify the deviations from the mean of price. Thus SD will rise strongly when prices are far from the mean of a specified look back period. This is another way of saying that prices are trending in one direction. As it is our goal to detect so called “good volatility” or trend volatility, SD is appealing as an adequate measure.

b) Standard Deviation and its applications

SD is probably the most widespread measure for analysing how dispersion data. There are many applications in mathematics and statistics so it is very well explored and can be used to compare any kind of data. Together with assumptions about the general distribution of data it helps to determine the characteristics of a price distribution. It is defined as:

\[
SD = \sqrt{\frac{\sum_{i=1}^{N} (Price_i - \mu)^2}{N}}
\]

with \(\mu\) as average of the data during the past \(N\) periods.

John Bollinger uses SD in order to construct a measure of relative highness and relative lowness of prices by adding and subtracting a multiple of SD from or to a moving average. These so called Bollinger Bands are a well-known tool for examining price and trend developments. Together with other indicators they provide a powerful tool for assessing if a market trend is more likely to continue than to reverse. Furthermore, SD can also be used to construct trailing stop systems, which will adapt to the volatility of a market and give trading strategies enough room for drawdowns.

c) Average True Range and its applications

The concept of True Range and its application as a technical indicator have been published by J. Welles Wilder jr. in his book “New Concepts in Technical Trading Strategies”. It can be derived from the idea that a measure of volatility during a period could be defined as the highest value during the period minus the lowest value. This trading range neglects the fact that prices tend to jump from time to time so that the lowest value of a period is still above the previous day’s market action. As a result the idea of True Range (TR) arose, which is defined as the greatest of the following:

1. High–Low
2. High–Previous Close
3. Low–Previous Close

To form an indicator of volatility TR is averaged over a specified period. Wilder recommended a period of 14 days and defined a volatility measure called volatility index as:

\[
VI_t = \frac{13 * VI_{t-1} + TR_t}{14} = ATR
\]

\[\text{Figure 1: Simple trend phase} \quad \text{Source: Tradesignal, own data.}\]
**Figure 2:** Trend reversal Source: Tradesignal, own data.

**Figure 3:** Trend reversal with gaps Source: Tradesignal, own data.

**Figure 4:** Rising price range Source: Tradesignal, own data.
A simple average of the first 14 periods is used to calculate the initial Volatility Index. The index is then calculated with an exponential moving average of the previous true ranges. This volatility index has since been better known under the name of Average True Range even though there can be slight differences in the calculation. Wilder used an exponential weighting while most technical analysis packages now use a simple arithmetic average for the calculation of ATR. ATR and Volatility Index will be used synonymously in this paper.

Wilder used ATR in a variety of ways. One of the applications was for a stop-and-reverse system, which deducted a multiple of ATR from the most favourable close during a trade he called “Significant Close.” This system was just named Volatility System as it was the most basic application of the Volatility Index. Another very popular application of ATR is the Directional Movement Index (DMI), which measures the directionality of a market by relating the biggest part of today’s trading range which is outside of yesterday’s trading range against the ATR. The calculations for this indicator will not be presented here, but one interesting application of the system should at least be noted. Wilders used an index called ADX (Average Directional Movement Index) to assess markets and their trend strength.

The idea of trading ranges can be found from the very early days of technical analysis. One of the popular systems which take advantage of this concept is the Keltner Bands or Keltner Channels. They were introduced by Chester W. Keltner in 1960 in his book “How To Make Money In Commodities”. He developed trading bands which were based on a moving average with a surrounding range constructed from what he called “typical price.” This typical price was calculated as the average of the high, low and close price of the period. As in most band systems the volatility measure was scaled by a factor (usually two) and added or subtracted from the mean. During the 1980s Linda B. Raschke modified the Keltner Bands and used ATR instead of the typical price average and used an exponential moving average instead of the simple moving average. Sometimes these band systems are called Keltner Channels, sometimes Keltner ATR Bands. In later chapters an ATR system will be used, which is a combination of both developments.

A simple moving average is used in order to receive comparable results, as from the Bollinger Bands and ATR—as defined above, this will be used as a volatility measure to construct the bands. During the course of the paper the constructed ATR band system and Keltner Channels should be regarded as synonymous, despite the minor differences in calculation.

In the following section the behavior of the introduced measures of volatility, SD and ATR, are observed and compared. Real world data is often too messy, so the start-off point is a simple data series that can be easily understood. References to applications of SD and ATR will be added to help readers recognize specific patterns, which are visible in application of Bollinger Bands in the case of SD or the Keltner Channels for ATR.

d) Theoretical analysis

The charts in this section are divided in four boxes with the most upper one presenting price development, the second showing the SD indicator, the third showing the ATR with a simple moving average and the lower box with the ATR indicator as defined by Welles Wilder with an exponential moving average. In this theoretical analysis, ATR with simple moving average is added as it is mathematically and graphically more easy to see the effects.

The first set of price movements shows the change from a sideward phase to a trending phase. All candles are identical, so the only change is in the direction of the movement. A change in the direction of a price movement cannot be discovered by ATR, but has a severe effect on SD which rises until the whole indicator period comprises the uptrend. All indicators have a time horizon of 20 days so the effect on SD vanishes after 20 days and SD stays on its higher level. From the chart it can be learned that the end of a sideward phase and the start of a new trend is accompanied by rising volatility. This means that e.g. Bollinger Bands are expected to widen in such a setting. John Bollinger notes that a sharp expansion of band width (meaning rising SD) from very low levels often marks “the beginning of a sustainable trend.”

In the second setting a trend reversal is depicted with constant candles. ATR will not change in this environment. In a first reaction SD will fall as a consequence of the trend change as the extremes during the period under review move closer together towards the average, which limits the square roots of the deviations of these observations from their mean. Only after half of the observation period (in our case 10 observations) has passed, volatility will rise again and finally reach its original level in the end (after 20 periods).

Bollinger Bands would thus contract in reaction to a change of the prevalent trend, before widening again as the new trend gains in range. In the real world such a setting is probably not often as key reversals are often coincided by higher trading ranges or small real bodies of candles, so ATR would be expected to show higher readings.

If a trend reverses and price gaps appear, it is often considered a critical phase for a price move. Even though the candles in the chart above are unchanged, they are moved apart to show gaps, which result in a higher ATR. From the first day of the new trend, ATR rises and marks the change in the price structure. The first day of the new trend distinguishes with a close benchmarked against the high of the uptrend. This is the reason why ATR rises up to the 21st day, before settling on the 22nd day as it can be seen in the ATR calculated with the simple moving average.

The SD, however, once again leads the change in price behavior as it adapts to the new environment. More generally it can be said as a rule of thumb, that SD will fall in the event of a trend reversal until the latest close in the opposite direction of the previous trend exceeds all other closes during the look back period.

There is one last building block left to observe. Until now we have not yet changed the candles themselves. At first the downtrend is weakening, so SD and ATR are both declining. SD is showing much more of a decline as it reverts back to zero from a very high level. If intraday variability picks up, then ATR shows this change at once, even if markets close just at the previous period’s close. This is an important insight as we can conclude that there is a fairly good chance that a breakout from a trading range could first be visible in a rising ATR before it
starts to show up in SD. Thus a breakout should first be visible in widening Keltner Bands before Bollinger Bands will follow.

Another conclusion that can already be drawn is that SD will generally be more volatile than ATR. While ATR is bound to the trading ranges of the market, SD depends on the closing prices and the distance from each other to rise. If ATR and SD are scaled to show the same mean then SD should show the greater variation for almost any market one could imagine.

e) Real world data

This section gives a very brief impression of the differences of the two selected measures for the markets under review in this study. The analysed markets, which will also be used for the evaluation of models based on SD and ATR, are:

- Global Equities:
  - S&P 500 as a global benchmark index
  - DAX as a German index
- Commodities: Oil prices measured by Brent oil (spot in order to avoid rollover gaps)
- Fixed Income Markets: 10y Bund-Future (back adjusted)

On the following pages (figures 5–8) a chart for each market is shown with the market index as a black line, the SD as a blue and ATR as an orange line. A red line separates the period before the financial market crisis from the crisis itself. The division between these two periods is set on January 1st 2008.

Table 1 shows again that ATR is generally lower than SD on average. Maximum and minimum values consistently vary more for SD than for ATR. Both equity charts are highly correlated and show similar percentage values for SD and ATR in table one. The oil market in figure 8 shows a very different picture: From a historic perspective SD and ATR both were relatively low, but exploded together with the oil price spike which began in the middle of 2007. This is also reflected in the high maximum percentage values of ATR and SD. All markets exhibit much stronger values of ATR or SD during the crisis times and most record levels reached were a multiple of the values seen before. The Bund future chart is special as high fluctuations in SD and ATR are much more common during all time periods. Maximum and minimum values are also rather close to the average.

<table>
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<th>S&amp;P 500</th>
<th>DAX</th>
<th>Bund Future</th>
<th>Oil</th>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
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<tr>
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<td>8.08</td>
<td>3.01</td>
<td>8.34</td>
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<tr>
<td><strong>SD (20)</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>Max / Min</td>
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<td>23.96</td>
<td>11.03</td>
<td>16.00</td>
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</table>

Model (1)

One possibility is to apply ATR and SD in a band system as it became popular with SD through John Bollinger’s Bollinger Bands or with ATR through Linda Bradford’s modification of the Keltner Channels. For the Bollinger Bands the “most elegant direct application” would be a volatility-breakout system. It has to be noticed that this kind of system normally needs prerequisites to give a trading signal. However, if one would apply such strict conditions, it would be very difficult to amass enough statistical data to gather a valid analysis, and trend phases would be excluded.

As a consequence the trading bands systems will be used as they are, despite the expectable poor performance. Every move outside of one of the trading bands is followed until prices reach the opposite trading band. In this analysis it is not the goal to construct a system which yields a high profit or an optimized trading system, but to compare the two volatility measures in the most pure way possible. The multiplication factor of SD will be kept at 2.0 as suggested for the Bollinger Band system, while the factor for ATR will be subject to a scaling factor as explained below.

Model (2)

A second approach will be used to validate the suitability of ATR and SD as volatility measures. A system which is permanently in the market would be a good starting point as it gathers enough statistical data material to be of significant meaning. Once again Wilders offers a good starting point with his volatility system, which is a stop-and-reverse-system (SAR system) based on ATR. It is a breakout system which does not rely on moving averages, but on distances from special points of the price history. From the “extreme favorable close price reached while in a trade” a multiple of ATR is added or deducted to construct a stop level for the trade. The prevailing trend is followed until the stop is hit and an opposite position is entered automatically. As this model was designed for ATR the multiplication factor of ATR will be kept at the original default of 3 and SD will be adapted if needed. The calculation period is set to 14 as in the original ATR calculation.

Adjustments

As this study is on the different reactions to price and trend changes, it is necessary to make figures comparable. A reasonable way is to scale ATR and SD on the same level so that averages will be the same. Thus the pure effect of a...
different measurement method will not be tainted by different levels of the volatility indicators. Details of this analysis can be found in the appendix.

4. Findings

As expected, the following table (table 2) illustrates that the trading bands are very slow systems, which do not generate many trades. On average there were not more than 3 to 5 trades per year.

It is interesting to note that both models scored best for the Bund future market with the most profitable trades and the best profit factors. Yet, it is intriguing that this is the only market where both models performed relatively worse during the time of the crisis. An explanation for this can be deducted from the findings of section 2e, where the Bund future showed the smallest variation of the measures over time and the most consistent volatility pattern. Figure 8 shows that SD is fluctuating strongly around ATR with greater variation than in the other pictures. This seems to be a favorable pattern for the Bollinger Band system.

With the exception of the Bund market and the Bollinger system for the DAX, both models were better during the crisis.
Volatility rose during the crisis and trends were very long
during the crisis and trends were very long
enduring. With regard to the profit factors from the two models,
no definite conclusion can be drawn from the data as to which
model performs best. Nevertheless there are some consistent
differences between the models which are quite striking. The
ATR band system seems to be the more robust approach as the
average profit even rose during the crisis time for every single
market. In most cases average profit even skyrocketed during
the time between 2008 and 2009 as, for example, in the S&P or
the oil market.

Maximum profits for all periods are also consistently higher
in every market for the Keltner system. It is interesting that the
maximum profit of the ATR system occurred right in the times
of crisis for all markets. Bollinger Bands mostly yielded their
biggest profit in 2008 to 2009, but not consistently, and the
difference against the previous maximum profit is not as large as
for the ATR system. Another fact of interest is that the Bollinger
Band system shows more trades than the Keltner model. This
applies to all time intervals under review. It appears that the
Bollinger System is more sensitive towards the market resulting
in trades being out more often than the Keltner system.

Differences between the two models become clear if an

Figure 7: Oil Source: Bloomberg data, own calculations.

Figure 8: Bund Future Source: Bloomberg data, own calculations.
example of a trade is reviewed. Figure 9 shows the most successful trade of the Keltner system on the DAX market. Starting on January 16th, 2008, the model stayed short until March 27th of the following year. From the chart it can be seen that the ATR system is not overly volatile. Bands do fluctuate in width and adapt to the markets, but have a very smooth appearance. The short position yielded a gain of 3271 points. In relation to the maximum price move, the system was able to recover 72% of the price range, an excellent result.

Interestingly the Bollinger Band system called to short the market in November 2007. Considering the time to mid of April the system was stopped out four times. This alone would not be too negative as stops also limit the risk of a trade. If all trades during this period are summed up then they show a performance of 1462 points—less than half of the performance of the Keltner system.

In figure 11 both band systems are plotted in the same chart. The blue area shows the Bollinger Bands and the golden area the Keltner Bands. Bollinger Bands show the greater variability, but this also means that they tend to narrow strongly if a market
reverses quickly. This can be understood by the theoretical analysis done in part two, which showed the behaviour of SD in case of a trend reversal. It is advantageous if a market reverses as the system is stopped out early on, but it seems that more often we should expect simply technical corrections from a major trend which do not end in a new trend.

Following are the results and review of the stop-and-reverse. The focus now shifts from profit factors, which are important for trading systems, to trades which prove to be favourable. In table 3 average profits are displayed, but our concern is the average winning profit. The logic behind this idea is that a stop-and-reverse system is generally not efficient in detecting trends and often has drawdowns. It can be compared to the Parabolic SAR, also created by Welles Wilder. Research from Robert Colby, though, suggests that the parabolic stop-and-reverse strategy in its original form is ineffective. How to spot a new trend exceeds the focus of this study. Ideas for this purpose can be derived from many textbooks. Focusing on winning trades, the answer is given to the question: How effective is a trailing stop system based on either ATR or SD with a good entry point?
Table 3 provides the results for the stop-and-reverse systems build on ATR or SD. All models showed higher winning profits during the times of the financial crisis, but this does not imply that average profits generally rose during the crisis. As stop levels are closer to the price action than in the band systems, trades are more frequent. Maximum profits occurred mostly during the crisis as for the band systems.

For most of the markets the ATR system shows more profitable trades and, generally, a higher average profit over the total observation period. As already stated these outcomes are of minor interest, but interestingly the picture for the winning trades is clear: For all markets and all time periods except for one (oil during the crisis) the ATR system provided higher average winning profits than the SD model.

5. Conclusion

In the first part of this thesis the differences between ATR and SD were explained and the mechanics of the volatility measures were analysed. SD can be slow in the case of trend reversals and often fails to detect new trends early on. ATR is much faster in the measurement of new trends, at least when accompanied by higher trading ranges, as is typical for trend reversals as seen in figure 3. From this conclusion it is clear that ATR is best suited to situations of dependence of volatility without correlation, as described by Benoit Mandelbrot. ATR would take full effect of high activity markets, regardless of their direction. These situations most often constitute a precursor of a new trend. SD is lagging and could be described as a confirmation of a new trend.

The second part of this study supports the theoretical analysis. Maximum profits are consistently higher for ATR in whatever testing model, for most markets using ATR show more profitable trades with higher average winning profits. ATR seems to be a better and more stable measure for a market’s activity. Especially during the times of high volatility ATR proved to be a slightly more robust measure than SD.

Coming back to the question of good or bad volatility, ATR appears to best adapt under conditions of extended trends. This is another expression for the so called good volatility. In sum the question, which is the title of this thesis, can generally be answered with yes. ATR seems to outperform SD in many circumstances.

A general result of the study is that both volatility measures, regardless of the model used, worked well during the financial crisis. Volatility was at high levels and trends endured, but also with many whipsaws. Interestingly, the relationship between ATR and SD remained stable during all time periods and in all markets. Further research might focus on the combination of these two volatility measures to detect and exploit the advantages of each. Additionally, such an analysis would be most interesting to determine significant market turning points or breakouts from sideward ranges.

6. Appendix

In tables 4–6, ATR and SD are compared during pre-crisis times (2000–2007) and within the major crisis time (2008–2009). There will be a comparison of the two measures for a 20-day horizon (a usual time horizon for SD) and a 14-day horizon (which is suggested by Welles Wilder for ATR). On the 20 day horizon ATR is generally smaller than SD and it is interesting that this relationship is relatively constant during different points in time. With the exception of the oil market, the relationship appears much the same for different markets. If pre-crisis levels are compared with crisis levels, it can
be seen that both measures of volatility react in almost the same manner. Both rise about 50% if compared to pre-crisis levels. The oil market is forming a specialty as it showed rapid price changes during the crisis. In consequence, volatility as measured by both measures rose about 160%.

ATR remains almost unchanged when the look back period is shortened. This is not overly surprising as every True Range is included in the calculation and averaged afterwards. Whether the 14-day average of a measure or the 20-day average of a measure is taken, it influences only the speed of the indicator reactions. SD on the other hand is much lower if the period is shortened. Also this result is not very surprising as deviations from the mean during a shorter period of time will be more limited than deviations from the mean of a longer period. For the examined period of 14-days, ATR and SD are almost on the same level. This is one of the first interesting results as it suggests that the 14 day period is a good basis for relative comparisons of ATR and SD.

During the further course of this paper the standard period for the two volatility indicators will be set at 14 days for the Volatility SAR system and at 20 days for the band systems. While the 14 day measure do not need adjustment, except for oil, the ATR of the band systems will be adjusted by a factor of 2.3 instead of 2.0 as used for SD. Measures of ATR will be scaled by 1.38 for the oil market, so the average deviation will be on the same level as SD.

### Table 4: ATR and SD characteristics for 20 day periods

<table>
<thead>
<tr>
<th>2000-2007</th>
<th>S&amp;P</th>
<th>ATR (20)</th>
<th>SD (20)</th>
<th>SD / ATR</th>
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<tr>
<td></td>
<td></td>
<td>16.20</td>
<td>19.23</td>
<td>1.19</td>
</tr>
<tr>
<td>DAX</td>
<td></td>
<td>97.18</td>
<td>115.66</td>
<td>1.19</td>
</tr>
<tr>
<td>Bund-Future</td>
<td>0.51</td>
<td>0.57</td>
<td>1.13</td>
<td></td>
</tr>
<tr>
<td>Oil</td>
<td></td>
<td>0.98</td>
<td>1.59</td>
<td>1.62</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>2008-2009</th>
<th>S&amp;P</th>
<th>ATR (20)</th>
<th>SD (20)</th>
<th>SD / ATR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>25.58</td>
<td>28.94</td>
<td>1.13</td>
</tr>
<tr>
<td>DAX</td>
<td></td>
<td>144.82</td>
<td>170.17</td>
<td>1.18</td>
</tr>
<tr>
<td>Bund-Future</td>
<td>0.83</td>
<td>0.87</td>
<td>1.06</td>
<td></td>
</tr>
<tr>
<td>Oil</td>
<td></td>
<td>2.53</td>
<td>4.12</td>
<td>1.63</td>
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</table>

### Table 5: ATR and SD characteristics for 14 day periods

<table>
<thead>
<tr>
<th>2000-2007</th>
<th>S&amp;P</th>
<th>ATR (14)</th>
<th>SD (14)</th>
<th>SD / ATR</th>
</tr>
</thead>
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<tr>
<td></td>
<td></td>
<td>16.21</td>
<td>16.48</td>
<td>1.02</td>
</tr>
<tr>
<td>DAX</td>
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<td>97.18</td>
<td>97.95</td>
<td>1.01</td>
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<td>0.51</td>
<td>0.48</td>
<td>0.94</td>
<td></td>
</tr>
<tr>
<td>Oil</td>
<td></td>
<td>0.99</td>
<td>1.36</td>
<td>1.38</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>2008-2009</th>
<th>S&amp;P</th>
<th>ATR (14)</th>
<th>SD (14)</th>
<th>SD / ATR</th>
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<tr>
<td></td>
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<td>25.47</td>
<td>24.79</td>
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<td>3.49</td>
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### Table 6: ATR and SD scaling factors for the models

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<tr>
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<th>SAR System</th>
<th>Band System</th>
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<td>SD (14)</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>3</td>
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<tr>
<td>DAX</td>
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<td>3</td>
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<tr>
<td>Bund-Future</td>
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<tr>
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7. References


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Keltner, Chester W., How To Make Money In Commodities, The Keltner Statistical Service, Kansas City, 1960

Software and data

Model building is done with Tradesignal Enterprise Edition, Tradesignal GmbH, Bremen, Germany
Tables and some charts are created with MS Office XP Standard Edition from Microsoft Corporation, Redmond WA, USA
Data for this study is provided by Bloomberg
The Volatility-Based Envelopes (VBE): a Dynamic Adaptation to Fixed Width Moving Average Envelopes

by Mohamed Elsaiid, MFTA

Abstract
This paper discusses the limitations of fixed-width envelopes and introduces a new method that addresses these limitations. The new method utilizes the concepts of standard deviation and correlation to produce a dynamic adaptation to the fixed-width envelopes. The paper also offers an example of a useful technique and some guidelines for applying the new method on price charts. The method will be referred to henceforth as the volatility-based envelopes (VBE).

Introduction

Fixed-Width Envelopes
Fixed-width envelopes (FWE) are two boundaries. Each is placed at a fixed percentage above and below a simple moving average (SMA) of the exact same duration. The primary aim of using the FWE is to contain the price action fluctuations and, hence, imply when prices have become over-extended in either direction. FWE are characterized by the same effects of lag and smoothness associated with their corresponding SMA.

Unfortunately, due to the inherent lag effect caused by the FWE, prices would quite often move and remain outside the envelopes' boundaries for a notable period of time. Despite some featured techniques adapted for the FWE that would accommodate and sometimes even depend on these occurrences, the initial purpose to contain the price action is not satisfied.

Bryan J. Millard suggested that in order to represent the trend properly and highlight active and dominant cycles using SMAs and FWE respectively, the statistically-correct plot would be to shift it back from the most recent data point by half the span of the SMA duration. This technique is referred to as centering the moving average. The rationale behind this is that since the FWE are properly plotted (centered), the price action fluctuations will be contained within the envelope boundaries.

To its credit, the centered FWE manages to contain a larger amount of price action. However, it still produces challenges. As a result of the centering procedure, the envelopes' values will terminate n-days prior to the most recent closing price, where \( n = (\text{SMA span} - 1)/2 \). Moreover, the centered FWE are non-adaptive to the continuous volatility changes of the price action. Depending on the price volatility, this will frequently cause the price fluctuations to move and remain out of the envelope boundaries (during high volatility phases), or even not react with the envelopes at all (during low volatility phases).

Another attempt to address the FWE’s lack of adaptability to price volatility was made in the 1980s by John Bollinger.

Adopting the statistical concept of standard deviation to the field of technical analysis, Mr. Bollinger introduced the Bollinger Bands (B-Bands). The B-Bands are two bands set at two standard deviations above and below a SMA calculated off the price action. In principle, the B-Bands aim at utilizing the standard deviation concept in order to identify rare and unsustainable price excursions and coin them as overbought (OB) and oversold (OS) conditions.

The B-Bands manage to contain more price action within its boundaries, especially during trendless phases in price action where identifying OB and OS conditions using the B-Bands become quite valuable. However, there are certain price conditions on the near to short term horizon as explained by Bollinger, in which prices tend to breakout and remain outside either one of the 2-standard deviation bands for some considerable time. At other times, even if the price excursion was relatively brief, the price gain (or loss) would be considerable. These conditions will generally occur during trending phases and following periods of low volatility in price action and are dubbed by John Bollinger as volatility breakouts.

The technique proposed by Bollinger relies on these volatility breakouts in order to initiate a position in the direction (favor) of the price breakout. Though very successful when properly identified in the price action, these volatility breakouts seem to argue against the general notion that price excursions occurring beyond two standard deviations are deemed rare and unsustainable.

Sustainable price breakouts from the B-Bands are primarily attributed to the difference in tendency and behavior of price action during trending vs. non-trending phases. During non-trending phases, price action visually exhibits a characteristic of oscillatory/mean reversion motion. During these events, price excursions are rare and unsustainable. While during trending phases, this feature becomes less dominant and further diminishes on the near to short term horizon as the trending phase grows stronger. This is attributed to the lagging effect of the SMA which visually appears clearer during trending phases. As you would recall from the B-bands calculation, the 2-standard deviations calculated are added to and subtracted from that lagging SMA to construct the upper and lower bands respectively. Hence, the B-Bands do not fully resolve the lag effect of the SMA.

Although the B-Bands succeed in achieving adaptability, the upper and lower bands do not inherit the smoothness of their corresponding SMA as they are relatively more erratic in motion than the latter. This does not allow them to be as suitable as centered FWE when attempting to highlight active and dominant cycles in the price action.
Introducing the adaptive Volatility-Based Envelopes (VBE)

Using volatility to achieve adaptability

To address the drawback associated with the lack of adaptability of the FWE, we use the measure of standard deviation. Unlike B-Bands’ calculation, we use the historical percent changes of price returns of a security instead of the historical price action of that security.

Practitioners in the field of statistics and financial engineering have hypothesized over the past decades that the percent changes in a stock price (or security) are normally distributed on the short term. Hence, we use this hypothesis as the basis for the VBE calculation methodology; once the standard deviation calculations were complete, the outcome was added to and subtracted from a SMA of the percent changes of price returns. Then, the outcome was added to and subtracted from today’s (the most recent) closing value on a percentage basis and not over a lagged SMA of the price action. As a result, a dynamic adaptation to the envelopes’ boundaries can be achieved, while avoiding the inherent lag effect of the MA of prices. The following steps will explain the VBE’s calculation methodology:

Step 1: Calculate the standard deviation (\( \sigma \)) of the percent changes (or logarithm) of the daily historical price returns (\( \sigma \)).

The standard deviation is calculated over duration of 21 daily percent change values.

Step 2: Calculate the values of the raw Volatility-Based Envelopes (raw VBE).

Example:

Assuming the following data:

The last given price (\( S \)) of the NASDAQ Index is: 2,190.

The simple average (\( \mu \)) of the percent change is: 0.07%.

The (\( \alpha \)) of the daily percent change is: 1.00%.

Therefore, we can expect that approximately 95.4% of the daily percent change movements to be maintained within the percentage range of:

\[ 0.07\% - (1.00\% \times 2) = -1.93\% \text{ (at 2 standard deviation)} \]

\[ 0.07\% + (1.00\% \times 2) = +2.07\% \text{ (at 2 standard deviation)} \]

To translate those values into a price range for most recent closing value of the index, or in other words, the raw VBE, then:

\[ 2,190 \times (1 - 1.93\%) = 2,147.7 \text{ (lower raw envelope at 2 standard deviation)} \]

\[ 2,190 \times (1 + 2.07\%) = 2,235.3 \text{ (upper raw envelope at 2 standard deviation)} \]

Plotting the raw VBE over the price chart

Using the same calculation method presented above, we can regress and calculate a daily range for all previous historical closing values of the S&P 500 Index and then plot the outcome as shown in Figure 1.

Figure 1 depicts the S&P 500 Index line chart with daily closing values and the raw upper and lower boundaries of the calculated raw VBE. As observed, there exists a strong (almost identical) similarity between the closing values (line chart) of the S&P500 Index and both the upper (red) and lower (blue)
boundaries of the calculated raw VBE. Having said that, both boundaries are choppy (raw), just as the index movement. Thus, a need to smooth out these boundaries is required.

**Step 3: Smooth the raw VBE using weighted moving averages**
To smooth out the raw VBE, we will use two centered weighted moving averages (CWMA) for both envelopes of the raw VBE. Using CWMAs instead of CSMAs mathematically results in a reduction of lag-time by approximately 40%. This means that instead of lagging the most recent price by \((\text{span} - 1)/2\) as with the case of the SMA, the lag is reduced to be approximately equivalent \((\text{span} - 1)/3.34\). In real life observations, and mainly due to the non-linear nature of price action, the lag tends to be reduced down to equate \((\text{span} - 1)/4\) instead of \((\text{span} - 1)/3.34\). This means that—in real life price action—the lag of the 21-period WMA tends to approximate to 5-periods (and in some cases, 4-periods), but not 6-periods.

<table>
<thead>
<tr>
<th>CWMA span</th>
<th>lag</th>
<th>periodic</th>
</tr>
</thead>
<tbody>
<tr>
<td>21.00</td>
<td>5.00</td>
<td></td>
</tr>
<tr>
<td>17.00</td>
<td>4.00</td>
<td></td>
</tr>
<tr>
<td>13.00</td>
<td>3.00</td>
<td></td>
</tr>
<tr>
<td>9.00</td>
<td>2.00</td>
<td></td>
</tr>
<tr>
<td>5.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>2.00</td>
<td>0.25</td>
<td></td>
</tr>
</tbody>
</table>

**Table 1** features CWMAs of different spans and the amount of lag attained by each.

The smoothed Volatility-Based Envelopes (VBE)
Now let us make a visual comparison between the smoothed VBE vs. both the centered FWE and the B-Bands. This comparison is shown in Figure 2.

Figure 2 depicts the advantages of the VBE over the centered FWE and the B-Bands. The centered FWE failed to mechanically adapt to volatility changes during the movements of the S&P 500 Index, while the VBE was able to contract and expand in accordance to the decrease and increase in volatility of the S&P 500 Index movements. Meanwhile, unlike the B-Bands, the VBE maintains its boundary smoothness, relative to the corresponding moving average of the price action. And finally, the VBE managed to contain more price action than the B-Bands. The VBE is constructed with the primary advantage of its ability to identify overbought (OB) and oversold (OS) conditions in the price chart regardless of the trend status.

**Step 4: Forecast the VBE’s missing data points using correlation**
To forecast the missing data points of the VBE, we use both the CWMA feature previously presented in Table 1, as well as the statistical concept of correlation \((\rho)\). The aim is to use the correlation between the values of other CWMAs of lesser span (independent variables) with the 21-period CWMA or smoothed VBE (dependant variable) to forecast the missing data points of that smoothed VBE. It's worth mentioning that all CWMAs of lesser span are selected with reference to the amount of their missing data points.

**Example:**
Using the daily values of the S&P 500 Index, we calculate \((\rho)\) matrix of the daily percentage change of a 21-day CWMA vs. the daily percentage change of a 17-day, 13-day, 9-day, 5-day and a 2-day CWMA over the most recent 63-actual data points as shown in table 2 (below).

<table>
<thead>
<tr>
<th>S&amp;P 500 Index — correlation coefficients ((\rho)) of 21, 17, 13, 9, 5 and 2-day % change of CWMAs</th>
</tr>
</thead>
<tbody>
<tr>
<td>(21\text{-CWMA})</td>
</tr>
<tr>
<td>21-CWMA</td>
</tr>
</tbody>
</table>

**Figure 2:** S&P 500 Index – Candlestick chart – Daily closing values – Normal scale
Using (σ) to forecast the missing data points of the 21-day CWMA

As previously explained, the 21-CWMA has 5 missing data points, while the 17-CWMA has only 4. This means that we can use the last given value of the 17-CWMA and the (σ) value of both variables from Table 2 to forecast the 1st missing value of the 21-CWMA as follows:

**Example:****

Referring to the data used in calculation, the last calculated percent change of the 17-CWMA was 0.80%. The last calculated value of the 21-CWMA was 1,122.30. The calculated (σ) value was 0.88 or 88% (from Table 2).

Then, the forecast of the 1st missing value of the 21-CWMA would be:

\[1,122.30 \times [1 + (0.80\% \times 0.88\%)] = 1,130.38.\]

This value is placed shifted back from the most recent closing value of the index by 4-days (since the 17-CWMA has only 4 missing data points).

Moving onwards, the following table (Table 3) shows the last calculated percent changes of the 13, 9, 5 and 2 CWMA as well as the forecast of the 2nd, 3rd, 4th and 5th (i.e. last) missing values of the 21-CWMA:

<table>
<thead>
<tr>
<th>Table 3</th>
<th>13-CWMA</th>
<th>9-CWMA</th>
<th>5-CWMA</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>0.86%</td>
<td>1.07%</td>
<td>0.93%</td>
<td>0.80%</td>
</tr>
<tr>
<td>1,137.80</td>
<td>1,145.99</td>
<td>1,151.90</td>
<td>1,154.77</td>
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</table>

Using that same concept, we can now forecast the five missing data points of the smoothed VBE.

Figure 3 depicts the smoothed VBE (at 2-standard deviation) with a forecast of its missing five data points using the correlation methodology previously presented.

**Using the VBE to identify over-extended price action on the price charts**

Now that the VBE has been constructed, we will demonstrate a useful trading technique when applying it to price charts. Below are some essential guidelines to be followed when using the VBE.

- Spot the most recent turning phase of the VBE (crest or trough) while it is occurring. The turning phase must be associated with a price excursion. The VBE will guarantee to a high degree that any price excursions are unsustainable regardless of the trend.
- If a price excursion occurred at a low, wait for the price to return back inside the VBE range, and then initiate a long position (or buy-back an old short position) until the next VBE turn (in the opposite direction) takes place.
- If a price excursion occurred at a high, wait for the price to return back inside the VBE range, and then short, sell or reduce your position until the next VBE turn (in the opposite direction) takes place.

 Needless to say, the appropriate trading strategy applied will depend on the direction of the prevailing trend direction. The following example (Figures 6 and 7) illustrates how to initiate buy and sell trades using the VBE.

**Figure 3:** S&P 500 Index – Candlestick chart – Daily closing values – Normal scale
Figure 4: EGX 30 Index – Candlestick chart – Daily closing values – Semi-log. scale

Figure 5: EGX 30 Index – Candlestick chart – Daily closing values – Semi-log. scale

Figure 6: NASDAQ Index – Candlestick chart – Daily closing values – Semi-log. scale
Conclusion

The VBE introduced in this paper dynamically adapts to the volatility changes of the price action and thus, successfully contains the price action within a predefined standard deviation range. Accordingly, the VBE is consistently able to identify over-extended price action regardless of the trend status. This is achieved without compromising the smoothness of its boundaries.

Nevertheless, the VBE is still left with a few challenges. Most importantly, is the fact that the most recent data points on the smoothed VBE are missing and required a forecast. In this paper, we used the concept of correlation and applied it to moving averages of different durations in order to achieve a reliable forecast for the missing data points. Still, the correlation figures tend to lose their significance as they approach zero, since a value of zero implies no correlation between the variables. Thus, the significance of the VBE estimated values will vary depending on the significance of the correlation figures, which tend to change more often than not. Thus, one should always check the (E) matrix values for statistical significance (i.e. at least above 0.5 and/or below -0.5).

References


Bibliography

VIX White Paper, Chicago Board Options Exchange (CBOE), 2009.
Data courtesy of Bloomberg and Reuters.
Charting software courtesy of Equis International MetaStock v.9.1.

Figure 7: NASDAQ Index – Candlestick chart – Daily closing values – Semi-log. scale
The world has experienced many financial crises, from the South Sea bubble in the early 18th century, to the Great Depression in early 20th century, to the Dot Com Crash in the early 21st century, to the housing and credit crisis in more recent years. It was the latter two crises which prompted author Perry Kaufman to consider alternative financial markets trading strategies that require more complex positions other than just long or short, but which he suggests rewards the trader with safety during a market collapse. The result of Kaufman’s deliberations is the book *Alpha Trading: Profitable Strategies That Remove Directional Risk.*

According to Kaufman the focus of this book is on the active trade, and the trading strategies employed are called Statistical Arbitrage or StatArb, which is the trading basis of many of the large hedge fund managers throughout the world. Statistical arbitrage is a market neutral trading method where a trader takes advantage of the expected mean reversion of the relationship between two co-integrated securities. Effectively, by cancelling out Beta (the overall market’s contribution to a security’s return) and trading Alpha (the active return of a security), a trader can feel confident and expect positive returns during extremely volatile periods of market activity. In this book, Kaufman takes the reader on a journey through formulae and examples to illustrate effective methods for achieving trading returns with lower risk profiles.

The book begins by contemplating the importance of price noise in a market with Kaufman examining the “drunken sailor walk” and the efficiency ratio, and quickly moves to a substantial section on the process of trading pairs of securities—initially equities and then futures. Examples are thorough and provide a good basis to understanding the process. Sample spreadsheets are provided on a website link referred to in the book.

In the following chapter Kaufman examines longer term pairs trading where price noise is usually not dominant and where well defined trends tend to emerge. The relationships between Dell and Hewlett-Packard and gold and platinum are used as examples. Cross market trading is also examined with a focus on the use of the “stress indicator”.

*Alpha Trading* is similar to Kaufman’s previous books, *New Trading Systems and Methods* and *A Short Course in Technical Trading*, in its examination of the quantitative aspects of trading, but it departs by not using Technical Analysis as the focus of the strategies. It provides well explained, robust methods for traders considering alternative quantitative trading strategies.
Having reviewed *The Heretics of Finance* for the 2010 issue of the *IFTA Journal* it was with great anticipation that I began reading this work by the same authors. While written from an entirely different slant, this new endeavour did not disappoint.

As the name suggests the authors investigate the path of technical analysis through the epochs, but the book reveals far more than this. History lovers amongst us, they will not be let down as Lo and Hasanhodzic succeed in tracing the origins of technical analysis back to the ancient Babylonian times, leading most of us on a fascinating path of new ideas and discovery.

When chronicling and signposting the stages in the developments for technical analysis, parallels are drawn to historical breakthroughs in civilization. The legendary and great contributors to the technical analysis are the markers along the way. This lends the book a reference quality as Lo and Hasanhodzic quote authors of some of these fabled works, providing the novice with an excellent starting overview, and reference points for their technical studies.

It is beyond the purpose of this book to cover the techniques and methods of technical analysis in depth. Nor do the authors claim to be technicians in their own right. And as an aside, this may be why the authors refer to technical analysis as a "craft" in this historical overview of Technical Analysis instead of an intellectual skilled discipline exercised with crafts and tools of the discipline. Lo and Hasanhodzic do present an objective view of the great debate on the validation of technical analysis. They track the history of technical analysis, but go much further and investigate and propose possible holes in the Efficient Market Hypothesis (EMH) and the Random Walk Theory. "A growing number of finance academics are coming to recognise that efficient markets are not an adequate model of reality. Thus, a crack in the door has been opened for academic considerations of technical analysis".  

The authors go on to suggest that Lo’s "adaptive markets hypothesis offers an internally consistent framework in which the EMH and behavioural biases can coexist" and that the implications of such are significant for technical analysis and its credibility.

In essence, *The Evolution of Technical Analysis* passes one of the most important tests as it motivates its readers to find out more on this fascinating subject.

The review copy was provided courtesy of John Wiley & Sons Australia and organised through the Educated Investor Book shop, Melbourne, Australia (see advertisement on page 40).

**Endnotes**

2. Ibid, p.164
Author Profiles

Robin Boldt, MFTA, SAMT
Robin is a Sales Trader for Swiss Equities at UBS Investment Bank, Zurich. He began his career in the field of Technical Analysis in 2002 at JRC Capital Management in Berlin as a Technical Analyst before he joined Goldman Sachs’ one delta trading team in Frankfurt until 2009.

As a sales trader Robin successfully implements Technical Analysis not only to improve his execution quality but also embeds different tools of the Technical Analysis within his equity recommendations. And despite the fact that trading and execution quality has become more and more dependent on electronic algorithmic trading capabilities, he is fully convinced that Technical Analysis gives traders and investors a meaningful advantage.

Breakouts are of particular interest for him. His work aims not only at the profitability of price channel variations, but also reminds of the fact that other parameters surrounding the core trading strategy influence the trading profitability significantly.

Mikael Bondesson
Mikael Bondesson, born 1977, holds a Degree of Master (One Year) of Science in Business and Economics with a major in Economics from the Lund University, Sweden. He currently works as a sales trader and advisor within Private Banking at Ålandsbanken Sverige AB, where he advises private clients and smaller institutional investors. His work also includes producing technical analysis within the bank; holding seminars and workshops; training private clients, institutional investors and colleagues in technical analysis. Mikael is a member of the Scandinavien Technical Analysts Federation (STAF).

Mohamed A. Elaasar, MFTA
Mohamed Elaasar is the Senior Technical Analyst and Market Strategist since 2003 at EFG Hermes Holding, the largest investment bank in the Middle East, and the cofounder of its Technical Analysis Department. He is currently responsible for issuing multiple types of technical research and reports covering Egypt and Gulf markets in the Middle East. He works with HNW clients, and provides technical training courses for the company’s staff. He was previously responsible for the US market analyst.

In 2009, he was grandfathered into the Society of Technical Analysts (STA) in UK.

He began his career in the field of Technical Analysis in 1995 at Pan Arab Investment in Cairo as a Technical Analyst till 2001. The scope of his work was mainly on global financial markets, including forex, commodities, etc.

Mohamed appears frequently in regional financial media channels and publishes articles about markets outlook.

John Gajewski
John Gajewski has 25 years experience in technical analysis and the foreign exchange, fixed interest and commodity markets. At the Commonwealth Bank of Australia he produced the successful Chartpoints commentaries, providing analysis and recommendations on forex, bonds and commodities to the bank’s traders and sales staff, institutional, corporate and business clients. He now produces The Chart Manager for Stafford Blue Pty Ltd.

John has also been an active participant in technical analysis education, working with the Australian Professional Technical Analysts Association, the Financial and Securities Industry Association and Kaplan Professional in developing and running technical analysis courses.

Regina Meani, CFTe
Regina covered world markets, as technical analyst and Associate Director for Deutsche Bank, before freelancing. She is an author and has presented internationally and locally and lectured for the Financial Services Institute of Australasia (FINSIA), Sydney University and the Australian Stock Exchange. She is President of the Australian Professional Technical Analysts (APTA) and immediate past Journal Director forIFTA. Regina carries the CFTe designation. She has regular columns in the financial press and appears in other media forums. Her freelance work includes market analysis, private tutoring, webinars and larger seminars, advising and training investors and traders in Market Psychology, CFD and share trading and technical analysis. Regina is also a past director of the Australian Technical Analysts Association (ATAA) and has belonged to the Society of Technical Analysts, UK (STA) for over thirty years.
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