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# The evolution of market timing


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## An innovative way to integrate technical indicators into a quant framework

In this report, we develop a trading system that starts with well-known technical trading rules, improves on them, and finally integrates them into a quantitative investing framework. One of the novel features of our approach is that it incorporates the direction of the broad equity market into its stock selection calls.

## Attractive performance across global markets

We construct monthly stock portfolios from our new technical signals. The long-short portfolio in the US market has an average monthly return of 2.0% from 1998-2013, with an annualized Sharpe ratio of 1.4. A long-only portfolio also performs consistently in Asia ex Japan, Europe, Japan, Emerging Markets, and other markets, with Sharpe ratios ranging from 1.1 to 1.6.

## Introducing the Quantitative Market Strength Index (QMSI)

We propose a Quantitative Market Strength Index (QMSI) to measure the bullishness or bearishness of the market. The QMSI shows strong market timing ability; a simple overlay of the QMSI can double the Sharpe ratio compared to the S&P 500. The current QMSI reading indicates a slightly bearish stance.


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# A letter to our readers

## Technically speaking

Technical analysis has always occupied a slightly mystical corner of the investing universe. Indeed the very mention tends to conjure up images of market magicians pouring over strange patterns with arcane names like "doji" or "shooting star". Not surprisingly, academics have always been particularly skeptical, with countless studies debunking the predictive power of technical indicators – including, we must confess, a study by one of your authors in a past life.[1]

However, notwithstanding academic snobbery, technical analysis has always occupied an important place in the practitioners' toolbox. In fact, in our own research, we have found value in technical signals, particularly when they are blended with the more traditional cross-sectional approach that quantitative investors tend to favor.[2] [3]

### Time-series versus cross-sectional

This latter point is worthy of further elaboration. To our mind, there is often little real distinction between a quantitative signal (i.e. a factor) and a technical signal. Both are essentially numerical patterns that, historically at least, had some ability to predict future returns. We might argue that a quant factor has some kind of underlying economic intuition, whereas a technical signal does not; but in the data-driven models used by many quants today this distinction is being eroded.[4] Instead, we think the most obvious delineation between a technical signal and a quant factor is that the former is typically used in a time-series context on a single security, while the latter is typically applied cross-sectionally, on many securities at a given point in time.

What does this mean? Let's use a simple example. A common technical indicator is moving average crossover. When the short-term moving average of a stock's price crosses the long-term moving average, we would buy the stock. In other words, we apply the rule to one stock at a time, and we are really comparing how that stock looks relative to its own history. Now take a simple quant factor like momentum. The way one typically trades this factor is to rank all stocks across the whole universe, and then buy a basket of the stocks that have performed the best in the past. In this case, stocks are compared relative to each other.

The technical analysis so loathed by academics is almost always of the time-series variety, i.e. apply the rule to many stocks in turn independently. In our past research, we found that a better way to use technical indicators is to use them cross-sectionally. To return to the simple moving average example, we could rank stocks based on how far away they are from triggering a buy signal on the rule, and then buy the basket of

[1] Cahan, R., J. Cahan, and B. Marshall, 2008,"Does intraday technical analysis in the US equity market have value?", *Journal of Empirical Finance*, Volume 15, Issue 2.

[2] Jussa et al, "Signal Processing: Technically savvy alpha", *Deutsche Bank Quantitative Strategy*, 6 May 2013

[3] Le Binh et al, "Quantiles: Technicalities in Asia", *Deutsche Bank Quantitative Strategy*, 17 November 2011

[4] See for example our N-LASR model, where we follow a purely data-driven approach and use machine learning algorithms to "learn" which patterns are being rewarded by the market with no regard to the underlying economic theory as to why a factor should or shouldn't work.

stocks that ranks best. Even the academics have started to grudgingly admit that that this cross-sectional approach may be a better way to use technical analysis.[5]

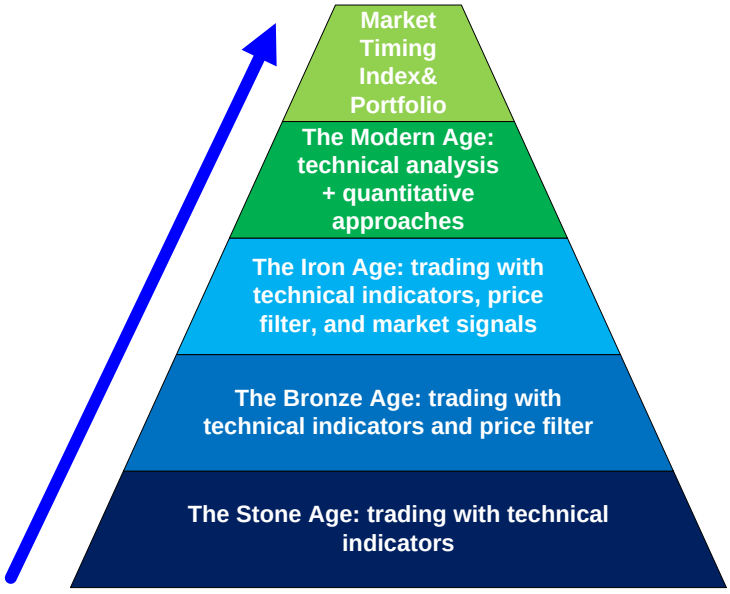
## The evolution of market timing

In this paper, we will also extend on the idea of using technical rules in a cross-sectional context by taking it one step further: can we use aggregate technical signals as a market timing tool?

As with individual stocks, the typical approach when using a technical rule to do market timing is to apply the rule to the market index. For example, in the previous moving average example we could just take the rule and run it on the past index level of the S&P 500 to get our buy and sell signals. But suppose instead we run the rule on all the constituent stocks of that index, and then aggregate to the market level? Does this give us a better timing tool than applying the rule at the market level?

The short answer is yes. In this paper we will show how to build a useful market timing signal step-by-step. We use the evolution of man as a useful analogy as we add each layer to our system (Figure 1). Starting with "Stone Age" tools – the individual rules at a single-stock level – we will evolve all the way to the "Modern Age" – a fully-fledged market timing system that we call the Quantitative Market Strength Index (QMSI).

Figure 1: The evolution of market timing




*Source: Deutsche Bank Quantitative Strategy*

We think the models described in the paper can be a useful starting point for quantitative investors looking to implement an uncorrelated mechanism for market timing.

Regards,

Yin, Rocky, Miguel, Javed, John, and Sheng
**Deutsche Bank Quantitative Strategy**

[5] Han, Y., K. Yang, and G. Zhou, 2011, "A new anomaly: The cross-sectional profitability of technical analysis", SSRN working paper, available at http://ssrn.com/abstract=1656460

# Stock screen

## Best long ideas based on our technical trading system

The screens below constitute our best trading ideas in the US, Canada, Japan, and UK markets, based on the system described in this report.

### Figure 2: Best long ideas in US

| Ticker | Company Name | Sector |
|---|---|---|
| ADBE | ADOBE SYSTEMS INC | Information Technology |
| AMAT | APPLIED MATERIALS INC | Information Technology |
| AMP | AMERIPRISE FINANCIAL INC | Financials |
| BIIB | BIOGEN IDEC INC | Health Care |
| CINF | CINCINNATI FINANCIAL CORP | Financials |
| CMA | COMERICA INC | Financials |
| CSC | COMPUTER SCIENCES CORP | Information Technology |
| DNB | DUN & BRADSTREET CORP | Industrials |
| FITB | FIFTH THIRD BANCORP | Financials |
| FLR | FLUOR CORP | Industrials |
| GE | GENERAL ELECTRIC CO | Industrials |
| HD | HOME DEPOT INC | Consumer Discretionary |
| IP | INTL PAPER CO | Materials |
| IVZ | INVESCO LTD | Financials |
| KEY | KEYCORP | Financials |
| MS | MORGAN STANLEY | Financials |
| MSFT | MICROSOFT CORP | Information Technology |
| MYL | MYLAN INC | Health Care |
| PFE | PFIZER INC | Health Care |
| PLL | PALL CORP | Industrials |

*Source: Deutsche Bank Quantitative Strategy*

### Figure 3: Best long ideas in Canada

| Ticker | Company Name | Sector |
|---|---|---|
| DOL | DOLLARAMA INC | Consumer Discretionary |
| PBN | PETROBAKKEN ENERGY LTD | Energy |
| FNV | FRANCO-NEVADA CORP | Materials |
| AIM | AIMIA INC | Consumer Discretionary |
| CSH.UN | CHARTWELL RETIREMENT RESID | Financials |
| KEY | KEYERA CORP | Energy |
| TFI | TRANSFORCE INC | Industrials |
| DH | DAVIS & HENDERSON CORP | Financials |
| MDA | MACDONALD DETTWILER & ASSOC | Information Technology |
| PPL | PEMBINA PIPELINE CORP | Energy |
| CJRB | CORUS ENTERTAINMENT INC | Consumer Discretionary |
| ALA | ALTAGAS LTD | Energy |
| WJA | WESTJET AIRLINES LTD | Industrials |
| CUF.UN | COMINAR REAL ESTATE INVT TR | Financials |
| GIL | GILDAN ACTIVEWEAR INC | Consumer Discretionary |
| REI.UN | RIOCAN REIT | Financials |
| FRU | FREEHOLD ROYALTIES LTD | Energy |
| REF.UN | CANADIAN REAL ESTATE INVT TR | Financials |
| CWT.UN | CALLOWAY REAL ESTATE INVT TR | Financials |
| WTE | WESTSHORE TERMS INVESTMNT CP | Industrials |

*Source: Deutsche Bank Quantitative Strategy*

### Figure 4: Best long ideas in Japan

| Ticker | Company Name | Sector |
|---|---|---|
| 1815 | Tekken Corp | Industrials |
| 1861 | Kumagai Gumi Co | Industrials |
| 1868 | Mitsui Home Co | Consumer Discretionary |
| 1885 | Toa Corp | Industrials |
| 1890 | Toyo Construction Co | Industrials |
| 1893 | Penta Ocean Construction | Industrials |
| 1911 | Sumitomo Forestry Co | Consumer Discretionary |
| 1944 | Kinden Corp | Industrials |
| 1950 | Nippon Densetsu Kogyo Co | Industrials |
| 2201 | Morinaga & Co | Consumer Staples |
| 2281 | Prima Meat Packers | Consumer Staples |
| 2602 | Nisshin Oil Mills | Consumer Staples |
| 3001 | Katakura Industries Co | Industrials |
| 3106 | Kurabo Industries | Consumer Discretionary |
| 3201 | Japan Wool Textile Co | Consumer Discretionary |
| 3333 | Asahi Co Ltd | Consumer Discretionary |
| 3407 | Asahi Kasei Corporation | Materials |
| 3433 | Tocalo Co Ltd | Industrials |
| 3436 | Sumco Corp | Information Technology |
| 3529 | Atsugi Co | Consumer Discretionary |

*Source: Deutsche Bank Quantitative Strategy*

### Figure 5: Best long ideas in U.K.

| Ticker | Company Name | Sector |
|---|---|---|
| BAB | Babcock Intl Group | Industrials |
| CAR | Carclo | Materials |
| CWK | Cranswick | Consumer Staples |
| DMGT | Daily Mail & General Trust A Nvtg | Consumer Discretionary |
| EZJ | Easyjet | Industrials |
| INCH | Inchcape | Consumer Discretionary |
| LSE | London Stock Exchange Plc | Financials |
| MGGT | Meggitt | Industrials |
| RB | Reckitt Benckiser Group PLC | Consumer Staples |
| SPD | Sports Direct International | Consumer Discretionary |
| SXS | Spectris | Information Technology |
| TALK | TalkTalk Telecom Group | Telecommunication Services |
| WTB | Whitbread | Consumer Discretionary |

*Source: Deutsche Bank Quantitative Strategy*

# The history of market timing

## Brief history of market timing

Every investor buys a security with the expectation its value will go up over time, and sells the security when the price of the security is expected to fall. Any rational investment is made to increase its value, and investors choose a time to buy and sell based on fundamental analysis, technical analysis, or quantitative research. In this sense, any analysis intended to gain from investment is a form of market timing.

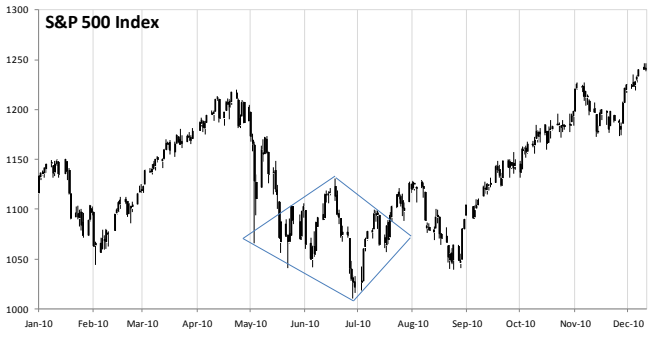
So, what is market timing? The market timing in this paper refers to the methods that investors use to predict the future direction of an asset's price, *using analysis based on technical indicators*. In this research, we use market timing and technical analysis interchangeable, and these two terms have the same meaning.

Technical analysis has been widely used in all type of markets for centuries. For example, Japanese rice traders in the 18th century used the patterns of candlestick charts to predict the price of rice. When the candlestick charts were introduced to the Western world, they were adopted as a visual market timing tool in stock, foreign exchange, and commodity trading. Figure 6 and Figure 7 show examples of two typical candlestick patterns, as studied in Edwards and Magee[6].

Figure 6: Candlestick pattern – head and shoulder top


*Source: Deutsche Bank Quantitative Strategy*

Figure 7: Candlestick pattern – diamond bottom




*Source: Deutsche Bank Quantitative Strategy*

In early days when there were no computers, traders drew lines, bars, and dots on paper, hoping to find patterns they could use to forecast the direction of a stock's price. The invention of computers and the internet has made the procedure of drawing these charts much easier. Charting software and historical data are widely available for free on the internet, and now only a few clicks are required to generate market timing signals. Of course, whether those signals actually work is another question.

Making investment decisions based on chart patterns may seem more like an art than science to many investors. After all, two individuals looking at the same chart often come up with completely different patterns. Some investors also attribute the successful cases of technical analysis to luck or data-mining. Is there really a way to generate alpha from technical analysis systematically? Our answer is yes, and in the following sections, we hope to show readers how to develop a systematic approach to market timing. Before we do though, it is worth reviewing the basics of technical analysis.

[6] Edwards, R. and J. Magee, "Technical Analysis of Stock Trends", 9th edition, BN Publishing

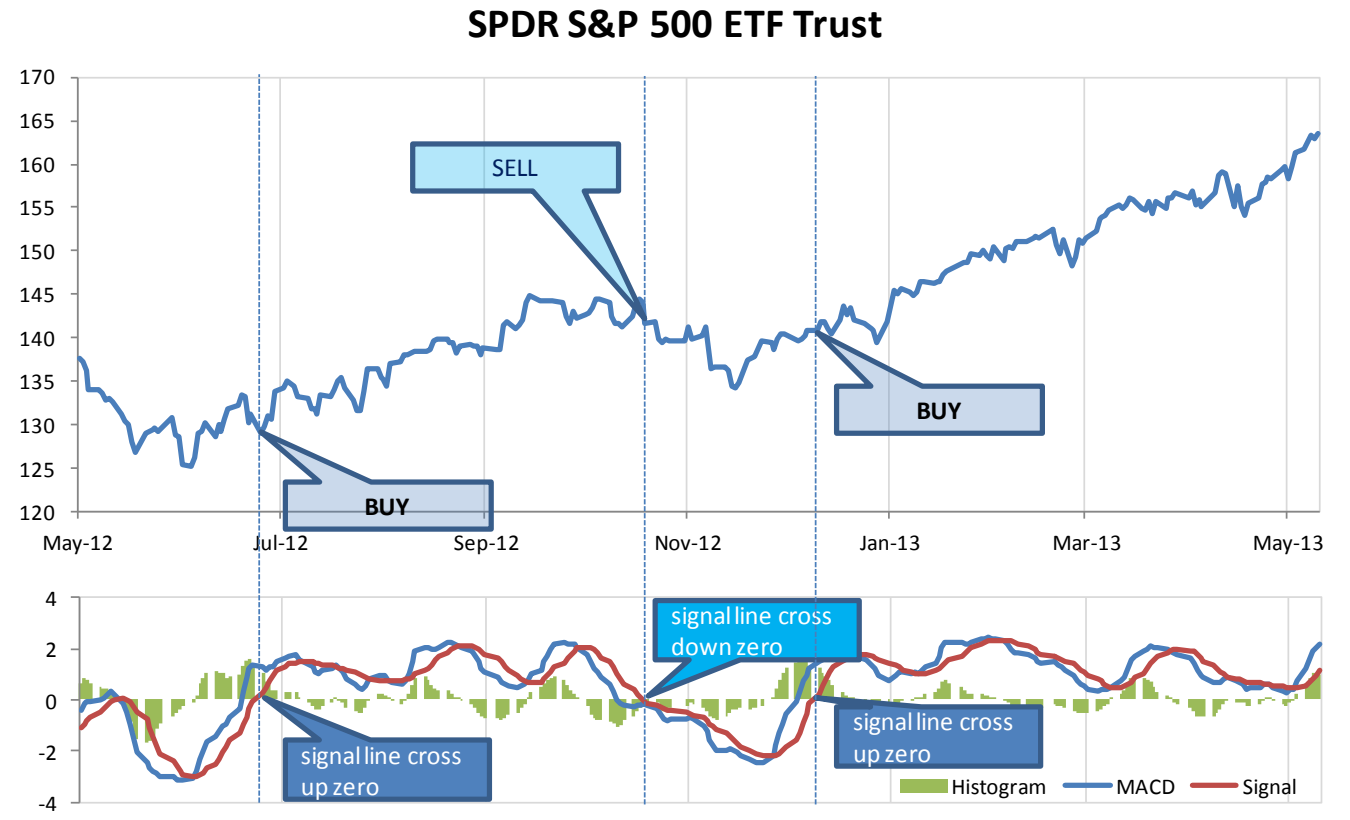
## Some simple examples of technical analysis

What is technical analysis? In a nutshell it is a trading system based only on past market action – usually price and sometimes volume as well. Consider a simple example.

### Follow the trend

Figure 8 shows the application of the MACD rule (Moving Average Convergence Divergence, we will discuss the details in the following sections) to the US market in recent months. The equity market in the US since July 2012 has exhibited steady up trends and down trends, which makes it the ideal playground for market timing. As shown in the chart, investors sticking to the rule would have been rewarded handsomely. Buy signals are triggered when the signal line of the MACD indicator cross above zero line and sell signals derive from points when the signal line falls below the zero line.

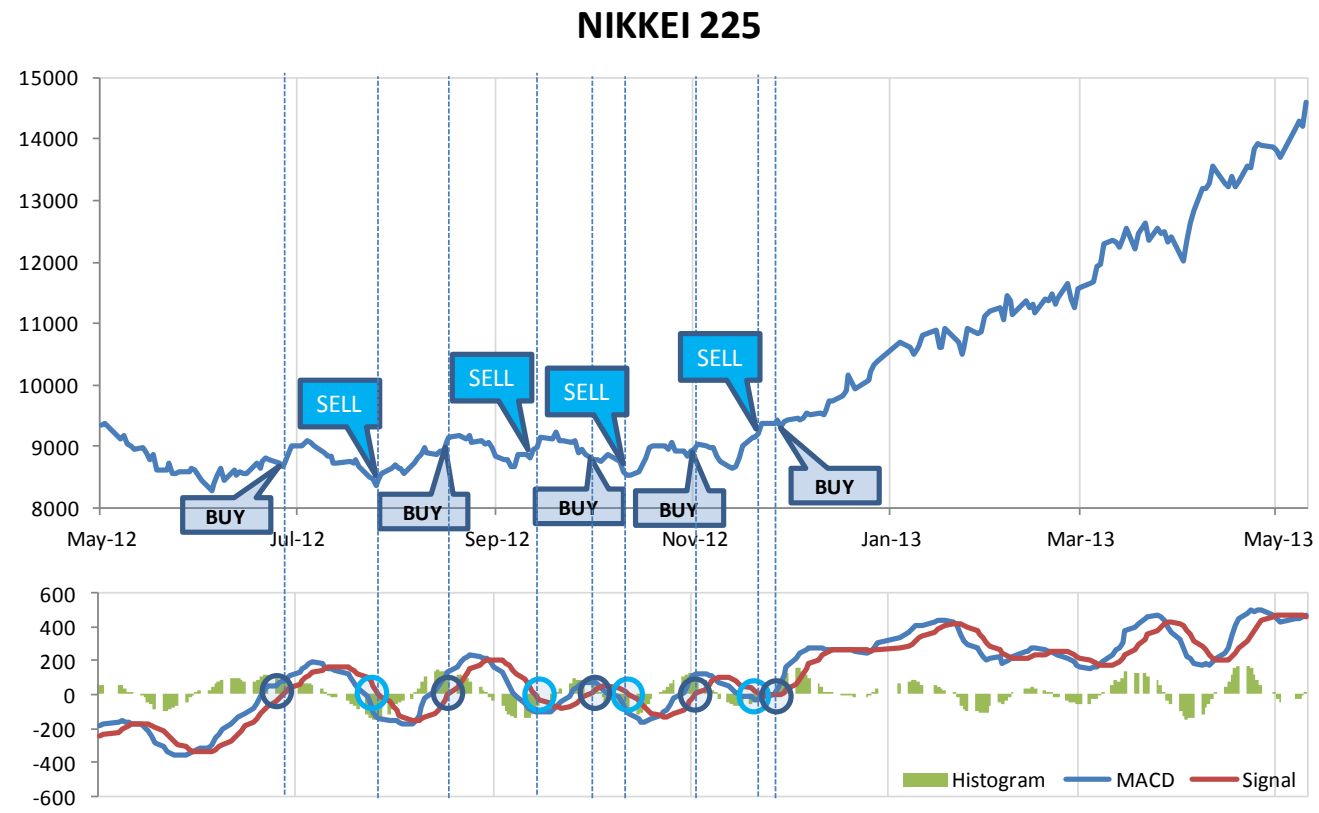
Figure 8: Market timing signals in US market




*Source: Deutsche Bank Quantitative Strategy*

However, we can always find a particular period and market where a given rule would have worked. If we apply the same rule to the Japanese equity market during the same period, the results are not nearly as compelling. We can see from Figure 9 that before the market took off in December 2012, all four buy signals and four sell signals were false turning points.

Figure 9: Market timing signals in Japanese market



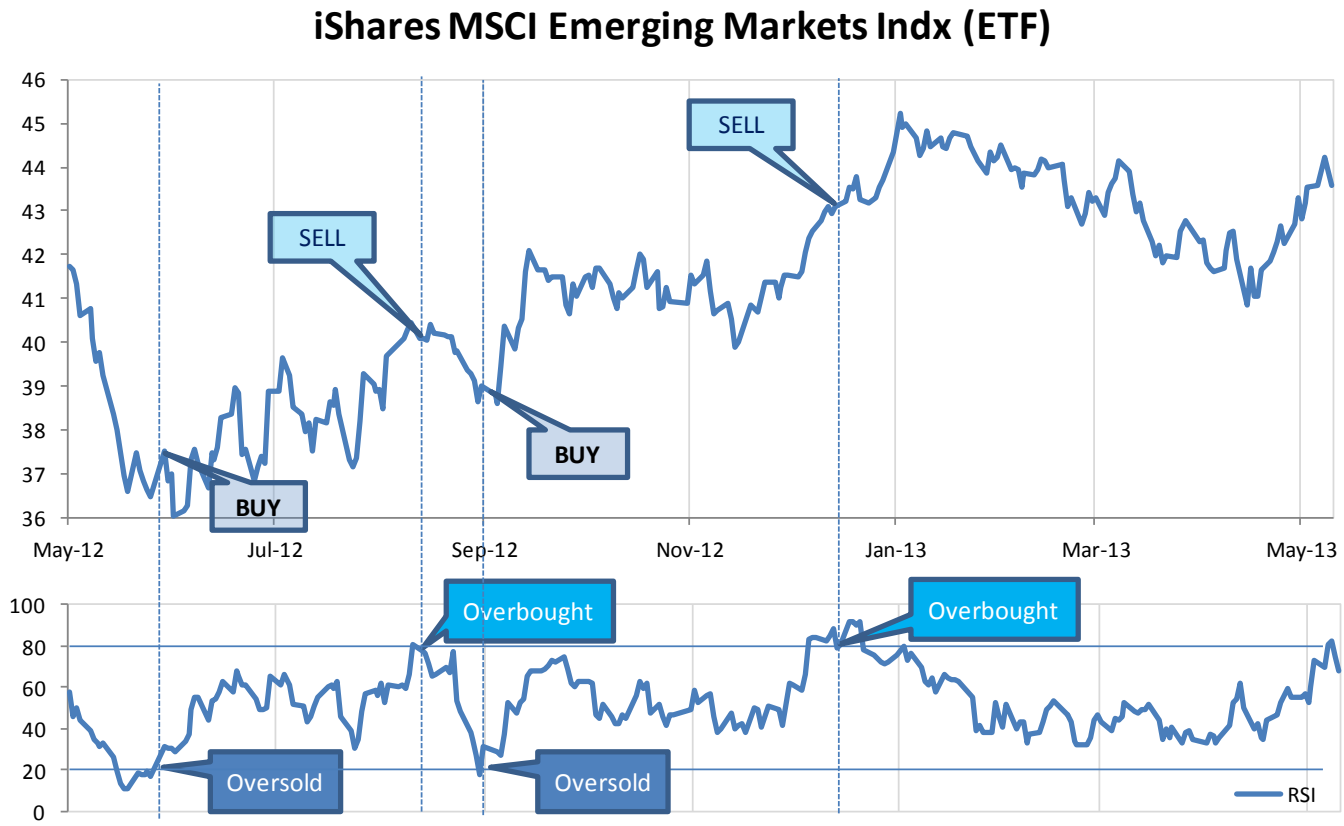

*Source: Deutsche Bank Quantitative Strategy*

A trading strategy based on the MACD indicator is a trend-following market timing strategy. This kind of strategy requires a persistent up or down trend spanning a certain period to profit; the Japanese market was moving sideways until the recent Bank of Japan announcement.

### Or don't follow the trend

Another type of market timing strategy is a reversal strategy, which uses technical indicators to pinpoint oversold points and overbought points. The relative strength index (RSI, details in the following sections) is one such reversal indicator, and is quite popular with market technicians. Figure 10 shows the trading signals on the iShares MSCI Emerging Markets Index Fund based on the RSI indicator. We can see that this reversal strategy has been working well since June 2012, but then again we can easily find another example where the RSI signal shows no predictive power.

Figure 10:Market timing signals on emerging market




*Source: Deutsche Bank Quantitative Strategy*

# The Stone Age

## Technical indicators are natural tools for market timing

People in the Stone Age used natural tools in their daily activities. Stones, sticks, and shells were not only abundant but also easy to use. Despite their simplicity, these crude tools still made our ancestors' lives easier.

In the investment world, technical indicators are natural tools we can use to predict the price trend of securities. Our previous study showed that technical indicators implemented with quantitative approaches have strong predictive power.[7] In this paper, our first step is to study if technical indicators can work on a single security. This is the time-series approach we mentioned in the introduction.

Technical indicators are generally classified to four types:

### Trend indicators

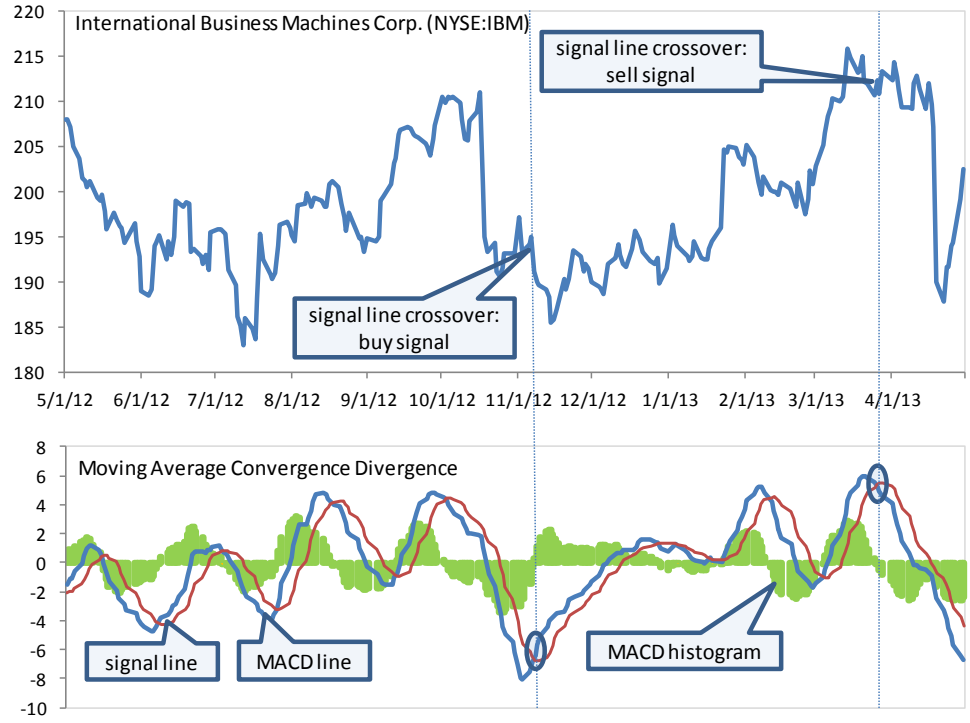
Trend indicators are used to identify price trends. The basic argument is that the "trend is your friend". Most trend indicators are derived from moving averages on the stock's price. Moving Average Convergence Divergence (MACD) is one of the most widely used trend indicators, and is the one we will use in this research.

- MACD is designed to capture the convergence and divergence of two moving averages of the stock price. There are actually three variables in the standard MACD indicator:
- MACD Line (MACD): The difference between 12-day exponential-weighted moving average of price and 26-day exponential-weighted moving average of price
- Signal Line (DEA): The 9-day exponential-weighted moving average of the MACD Line.
- MACD Histogram (DIFF): The difference between the MACD Line and the Signal Line.

The most common MACD signals are signal line crossovers. When the MACD Line turns up and crosses above the Signal Line, the uptrend is accelerating and the price is expected to move higher, therefore a bullish signal (Buy) is generated. By contrast, when the MACD Line falls and crosses below the Signal Line, investors see it as a sign the stock is losing steam and a bearish signal (Sell) is triggered. Some investors also use signals when the MACD Line crosses the zero line and the Signal Line crosses the zero line. The examples in Figure 8 and Figure 9 use signals from the Signal Line crossing the center line (zero line). We will use the signal line crossover in this research – see the example in Figure 11.

[7] Jussa et al, "Signal Processing: Technically savvy alpha", *Deutsche Bank Quantitative Strategy*, 6 May 2013

Figure 11: MACD




*Source: Deutsche Bank Quantitative Strategy*

## Momentum indicators[8]

Momentum indicators are designed to determine overbought and oversold positions. Technicians use momentum indicators to identify tops and bottoms in price action. William's %R (W%R or WR) and Relative Strength Index (RSI) are examples of momentum indicators.

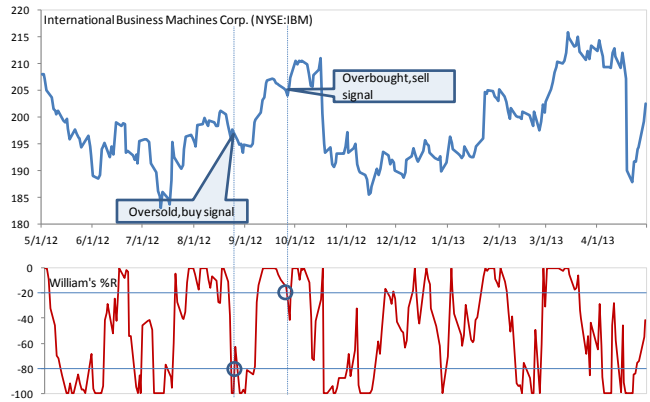
W%R measures the level of the close price relative to the highest high price for the look-back window. W%R ranges from -100 to 0, and is used to determine the overbought and oversold level of the security. The traditional thresholds for overbought and oversold are -20 and -80, respectively. A reading above -20 for the 14-day W%R would suggest the underlying stock is overbought compared to its 14-day high-low range, while reading below -80 would indicate the underlying security is oversold.

The Relative Strength Index (RSI) is another popular momentum oscillator that is used to measure the speed and change of price movements. The value of RSI is between 0 and 100, and similar to W%R, certain thresholds are set to determine whether the security is overbought or oversold. The widely used overbought threshold is 70 and oversold is 30.

The rationale for momentum indicators is that when the price moves to the period high, investors tend to take profits and reduce their holdings and hence the price will drop, and vice versa. Figure 12 and Figure 13 show examples of the W%R and RSI.

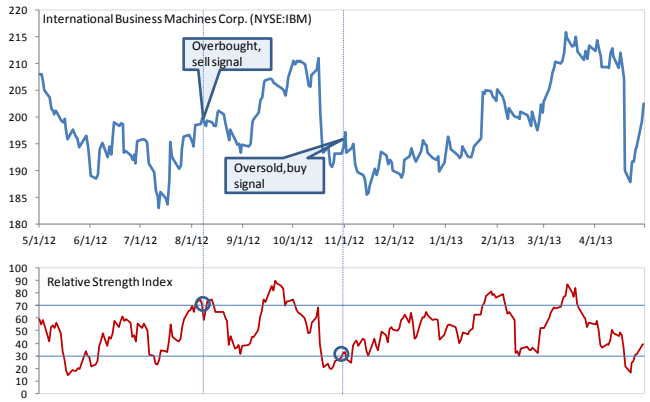
[8] Note that while technicians tend to call these "momentum" indicators, they are more like what would call "reversal" in traditional cross-sectional quantitative research, i.e. we believe prices will mean revert.

Figure 12: William's %R




Source: Deutsche Bank Quantitative Strategy

Figure 13: Relative Strength Index



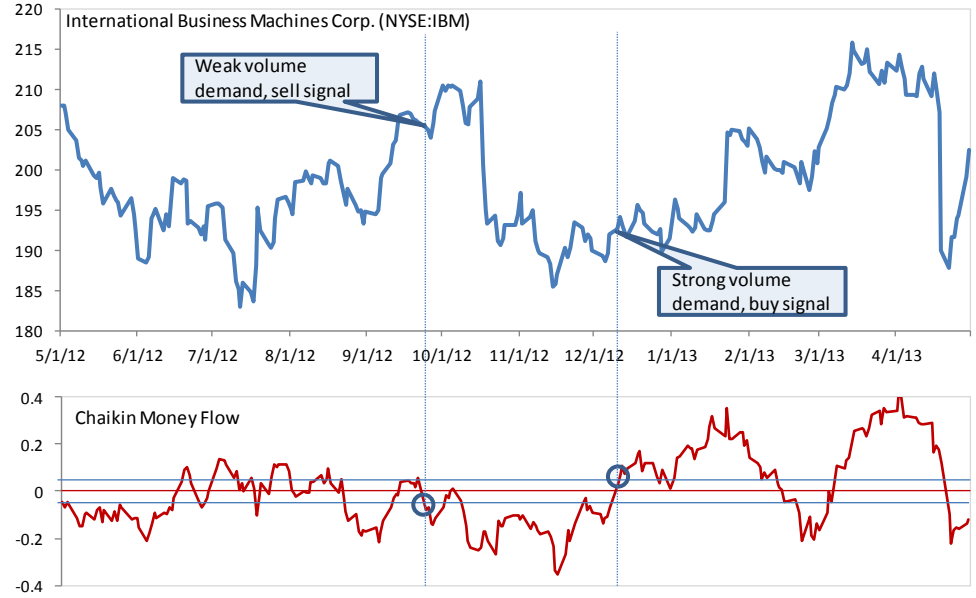

Source: Deutsche Bank Quantitative Strategy

## Volume indicators

Volume indicators combine information about the volume of trading with price patterns. Chartists believe that signals accompanied by high trading volume are stronger than signals based on low trading volume. Examples of volume indicators include Chaikin Money Flow (CMF) and the Money Flow Index (MFI).

CMF was developed by Marc Chaikin to measure the flow of funds into and out of a stock over a certain time period. The standard time period is one month. The rationale of this indicator is that increasing demand for a stock will push up its price, while weak demand will depress the price. Figure 14 shows the CMF in action.

Figure 14: Chaikin Money Flow

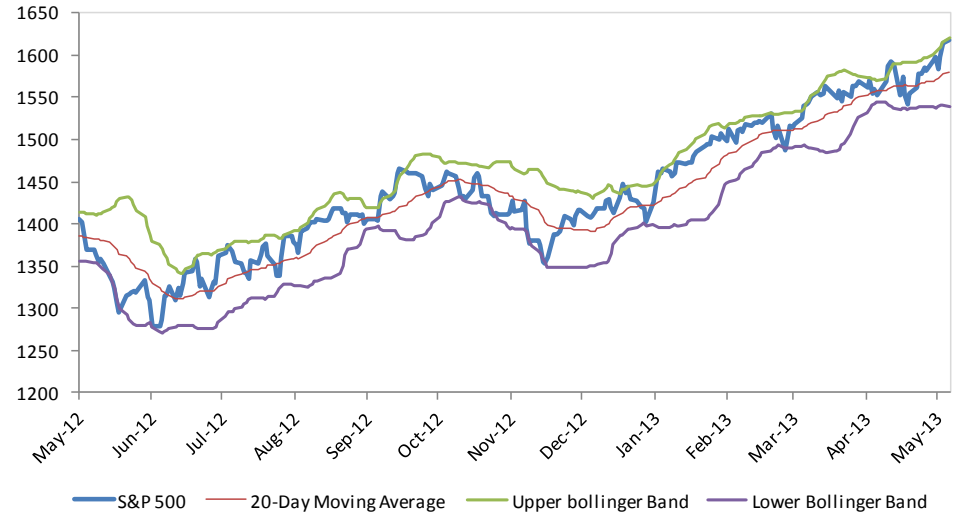



Source: Deutsche Bank Quantitative Strategy

## Volatility indicators

Volatility indicators integrate volatility of price and volume with price level. Bollinger Bands and the Average True Range rule are some of the widely used indicators in this group.

Figure 15: Bollinger Bands




*Source: Deutsche Bank Quantitative Strategyi*

## Scope of this research

In this paper it is not our intention to test every possible variation of these technical trading rules. Instead, our focus is on how to build a sensible market timing framework. With this in mind, we will focus on four directional indicators from the aforementioned four groups, and design trading rules that are widely used among traders. Since volatility indicators do not tell the direction of price movement, we exclude these indicators in this analysis. Figure 16 lists four technical indicators and their parameters that we use in this paper.

Figure 16:Technical indicators and trading rules

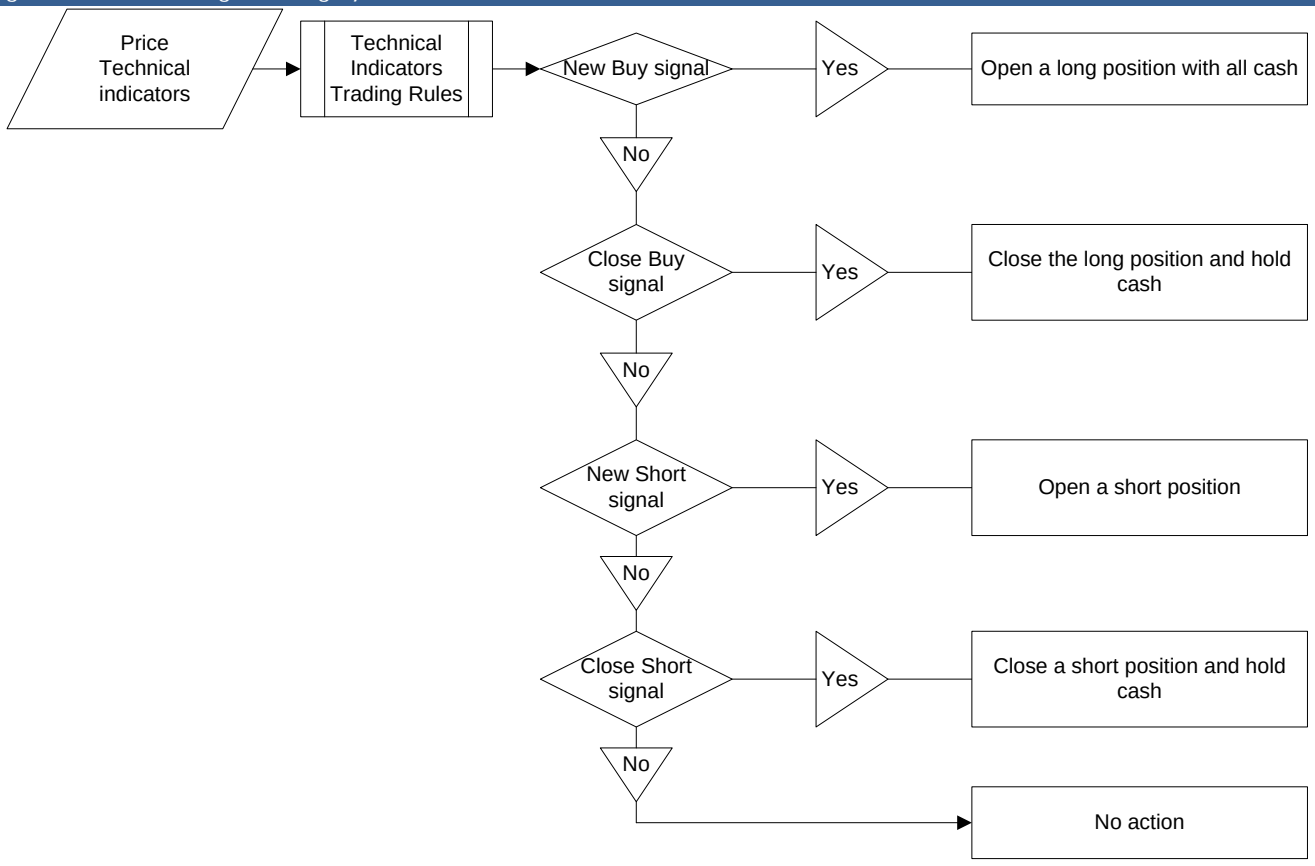
| Type | Indicator | Formula | Parameters | Trading Rules |
|---|---|---|---|---|
| Trend | MACD | MACD Line(MACD)= EMA(close,Short Moving Window)-EMA(close,Long Moving Window)<br>Signal Line(DEA)=EMA(MACD,Smooth Window)<br>MACD Histogram(DIFF)=MACD-DEA | Short Moving Window=12<br>Long Moving Window=26<br>Smooth Window=9 | 1. If DIFF drops below 0 from positive value, sell<br>2. If MACD increases above 0 from negative value, close sell<br>3. If DIFF crossovers above 0 from negative value, buy<br>4. If MACD drops below 0 from positive value, close buy |
| Momentum | Williams %R (WR) | W%R =- (high_over_Lookback_period - close) / (high_over_period - low_over_Lookback_period) | Lookback_period=21 | 1. If W%R drops below -20 from 0 to -20, sell;<br>2. If W%R drops below -80, close sell position;<br>3. If W%R increases above -80 from -80 to -100, buy;<br>4. If W%R increases above -20, close buy position. |
| Volume | Chaikin Money Flow | 1. Money Flow Multiplier = [(Close - Low) - (High - Close)] /(High - Low)<br>2. Money Flow Volume = Money Flow Multiplier x Volume for the Lookback_period<br>3. CMF = Sum of Money Flow Volume / Sum of Volume for the Lookback_period | Lookback_period=21 | 1. If CMF drops below -0.05, sell;<br>2. If CMF increases above 0, close sell position;<br>3. If CMF increases above 0.05, buy;<br>4. If CMF dropss below 0, close buy position. |
| Momentum | RSI | RSI = 100*RS/(1+RS) )<br>RS = Average Gain / Average Loss | Lookback_period=14 | 1. If RSI drops below 70 from 70 to 100, sell;<br>2. If RSI drops below 30, close sell position;<br>3. If RSI increases above 30 from 0 to 30, buy;<br>4. If RSI increases above 70, close buy position. |

*Source: Deutsche Bank Quantitative Strategy*

## The Stone Age setup

Since we are still stuck in the Stone Age, we are going to begin with the simple trading system shown in Figure 17. We will take each of the rules shown in the table above and apply them to each stock in turn; each stock is traded independently based on its own signals. Consecutive signals in the same direction are not traded if there is already an open position in that direction. Each position is held until there is a close signal or opposing signal.

Figure 17: A Stone Age trading system




*Source: Deutsche Bank Quantitative Strategy*

## Performance metrics

As the first step of this study, we backtest the trading signals based on each individual technical indicator on each stock in turn. Our universe in the US market is each stock in the S&P 500 Index, and our global universes are the stocks in each country-level S&P BMI index. Each stock in the universe is tested independently. One stock is traded only if on the signal day the stock is in the universe, but once a position is opened, the position will be held until there is a closing signal or inverse signal, regardless of whether the stock is still in the universe or not. We summarize the statistics from the backtesting in Figure 18, and return distributions are shown in Figure 19 to Figure 22, respectively.

In the table, the Average Return column is the average return per trade, while the Average Daily Return is the average return on each day a trade is open. The Winning Ratio is the percent of trades that yield positive returns. The Excess Return column is relative to the cap-weighted benchmark.

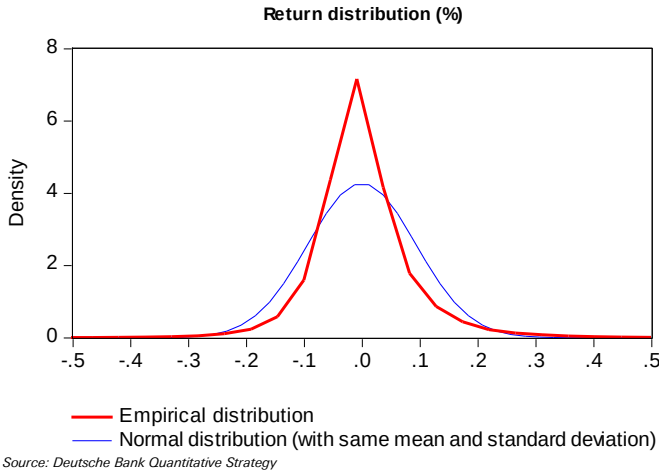
Note that the short side is adjusted for the fact one is going short, so a negative return indicates that the trades are, on average, losing money.

Figure 18: US Result Summary – Stone Age Individual Indicator Signals

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| MACD | Long | 79,577 | 0.48% | 14.9 | 0.032% | 47.7% | 0.03% |
| | Short | 79,721 | -0.65% | 15.1 | -0.043% | 39.6% | -1.08% |
| | **Total** | **159,298** | **-0.09%** | **15.0** | **-0.006%** | **43.6%** | **-0.52%** |
| WR | Long | 80,817 | 0.39% | 9.6 | 0.041% | 59.2% | 0.08% |
| | Short | 80,700 | -0.28% | 10.9 | -0.026% | 55.1% | -0.53% |
| | **Total** | **161,517** | **0.06%** | **10.3** | **0.005%** | **57.1%** | **-0.22%** |
| CMF | Long | 58,711 | 0.67% | 20.8 | 0.032% | 46.7% | 0.15% |
| | Short | 55,334 | -0.67% | 15.5 | -0.043% | 40.1% | -1.24% |
| | **Total** | **114,045** | **0.02%** | **18.3** | **0.001%** | **43.5%** | **-0.53%** |
| RSI | Long | 22,464 | 1.77% | 42.9 | 0.041% | 70.6% | 0.23% |
| | Short | 22,433 | -1.70% | 50.0 | -0.034% | 59.2% | -2.97% |
| | **total** | **44,897** | **0.04%** | **46.5** | **0.001%** | **64.9%** | **-1.37%** |

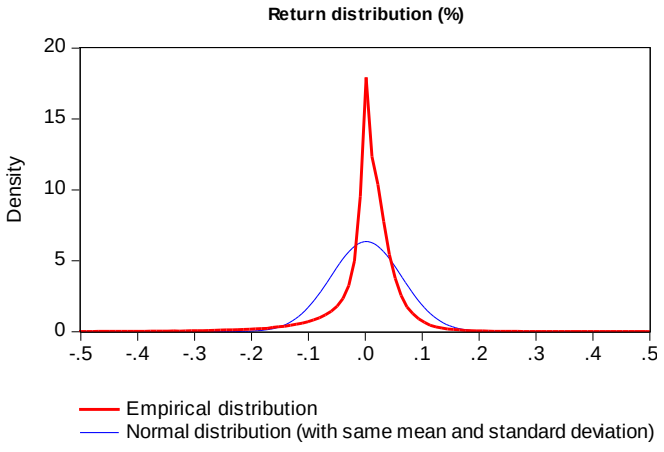
*Source: Deutsche Bank Quantitative Strategy*

Figure 19: US Stone Age MACD Signals



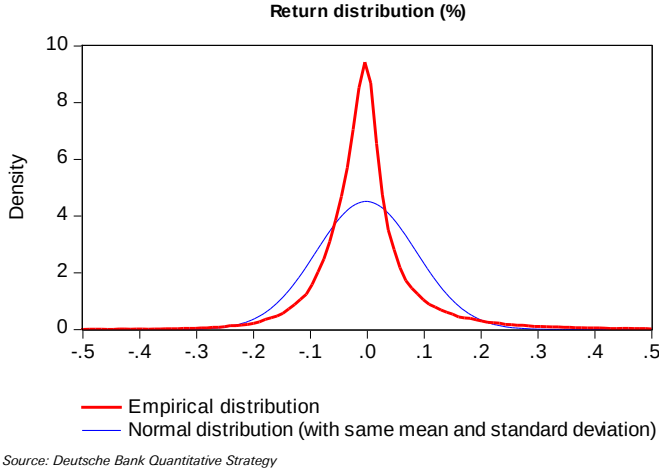

*Source: Deutsche Bank Quantitative Strategy*

Figure 20: US Stone Age WR Signals



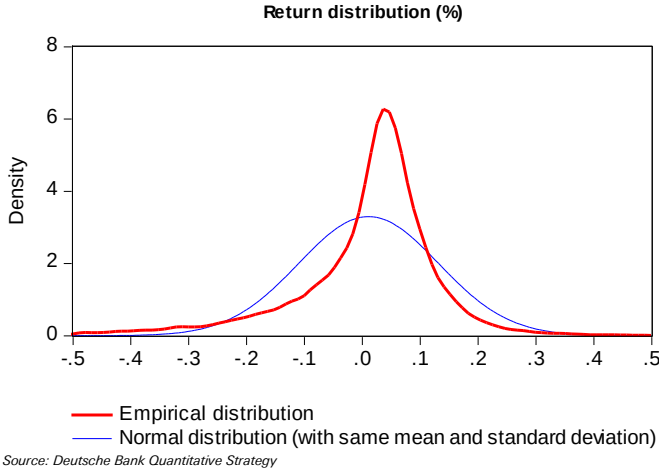

*Source: Deutsche Bank Quantitative Strategy*

Figure 21: US Stone Age CMF Signals




*Source: Deutsche Bank Quantitative Strategy*

Figure 22: US Stone Age RSI Signals




*Source: Deutsche Bank Quantitative Strategy*

Overall, the single technical indicators in the Stone Age do not generate consistent positive returns. However, it is interesting that Buy signals show some predictive power on average, particularly for the RSI indicator which can generate about 1.77% return per trade with a low turnover (the holding period is about two months on average). On the other hand, the Sell signal has been consistently wrong. One potential explanation is that most of the backtesting period from January 1995 to April 2013 consisted of bull markets, as shown in Figure 23.

Figure 23: S&P 500 Index


*Source: Deutsche Bank Quantitative Strategy*

We also conduct the backtesting in S&P BMI Japan universe, and results are consistent with those of US market. In this test, all stock prices and returns are local currency (Yen). Note that results for other markets are available on request.

Figure 24: Japan Result Summary – Stone Age Individual Indicator Signals

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| MACD | Long | 225,622 | 0.00% | 14.8 | 0.000% | 40.2% | 0.09% |
| | Short | 226,045 | -0.15% | 14.7 | -0.010% | 43.7% | -0.26% |
| | **Total** | **451,667** | **-0.08%** | **14.8** | **-0.005%** | **42.0%** | **-0.08%** |
| WR | Long | 223,158 | -0.14% | 10.9 | -0.013% | 51.2% | -0.13% |
| | Short | 221,189 | -0.21% | 9.8 | -0.022% | 53.9% | -0.23% |
| | **Total** | **444,347** | **-0.18%** | **10.3** | **-0.017%** | **52.5%** | **-0.18%** |
| CMF | Long | 156,225 | -0.12% | 19.2 | -0.006% | 41.4% | 0.09% |
| | Short | 157,075 | -0.26% | 19.1 | -0.014% | 44.3% | -0.44% |
| | **Total** | **313,300** | **-0.19%** | **19.1** | **-0.010%** | **42.8%** | **-0.18%** |
| RSI | Long | 53,477 | -0.39% | 66.6 | -0.006% | 58.4% | -0.05% |
| | Short | 52,403 | -0.38% | 40.5 | -0.009% | 63.4% | -0.50% |
| | **total** | **105,880** | **-0.39%** | **53.7** | **-0.007%** | **60.9%** | **-0.27%** |

*Source: Deutsche Bank Quantitative Strategy*

## Adding fuzzy logic

The results in the previous section suggest that the market timing ability of technical indicators is weak, and is in line with the skepticism among academic researchers.

However, technical analysis is widely used among traders around the world, who often base their decisions on multiple signals rather than one particular indicator. Therefore, a natural question is whether combining several indicators together can improve accuracy and performance. We are still in the Stone Age, but there's no need to be completely Neanderthal.

Since the output of a single technical signal is a string of buy and sell signals, we need rules to convert this binary outcome into a value or score that we can use when aggregating rules. We do this by introducing fuzzy logic. Fuzzy logic is a probabilistic logic that deals with reasoning problems, and is used to convert IF-THEN rules to values that can be applied to mathematical operations, i.e. addition and subtraction.

We design a fuzzy logic function for each indicator we tested in the previous section, based on the trading rules listed in Figure 16. The outcomes of each fuzzy logic function are: 1, 0.5, -1, and -0.5, representing buy, close buy, sell, and close sell signals. Four fuzzy logic functions can be defined based on the rules listed in Figure 16:

- Fuzzy logic function for MACD indicator:

$$S_{MACD_t} = \begin{cases} 1, DIFF_{t-1} > 0 \text{ and } DIFF_{t-2} < 0 \\ 0.5, MACD_{t-1} < 0 \text{ and } MACD_{t-2} > 0 \\ -1, DIFF_{t-1} < 0 \text{ and } DIFF_{t-2} > 0 \\ -0.5, MACD_{t-1} > 0 \text{ and } MACD_{t-2} < 0 \end{cases}$$

- Fuzzy logic function for William's %R indicator:

$$S_{WR_t} = \begin{cases} 1, WR_{t-1} > -80 \text{ and } WR_{t-2} < -80 \\ 0.5, WR_{t-1} > -20 \text{ and } WR_{t-2} < -20 \\ -1, WR_{t-1} < -20 \text{ and } WR_{t-2} > -20 \\ -0.5, WR_{t-1} < -80 \text{ and } WR_{t-2} > -80 \end{cases}$$

- Fuzzy logic function for Chaikin Money Flow indicator:

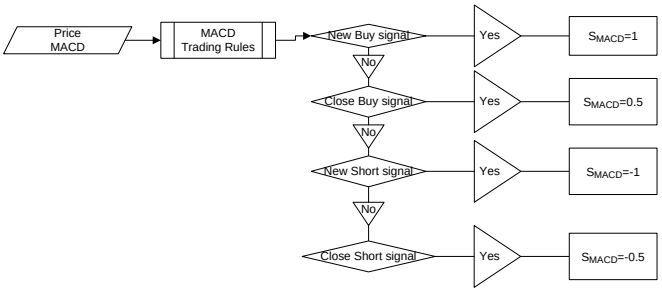
$$S_{CMF_t} = \begin{cases} 1, CMF_{t-1} > 0.05 \text{ and } CMF_{t-2} < 0.05 \\ 0.5, CMF_{t-1} < 0 \text{ and } CMF_{t-2} > 0 \\ -1, CMF_{t-1} < -0.05 \text{ and } CMF_{t-2} > -0.05 \\ -0.5, CMF_{t-1} > 0 \text{ and } CMF_{t-2} < 0 \end{cases}$$

- Fuzzy logic function for Relative Strength Index indicator:

$$S_{RSI_t} = \begin{cases} 1, RSI_{t-1} > 30 \text{ and } RSI_{t-2} < 30 \\ 0.5, RSI_{t-1} > 70 \text{ and } RSI_{t-2} < 70 \\ -1, RSI_{t-1} < 70 \text{ and } RSI_{t-2} > 70 \\ -0.5, RSI_{t-1} < 30 \text{ and } RSI_{t-2} > 30 \end{cases}$$

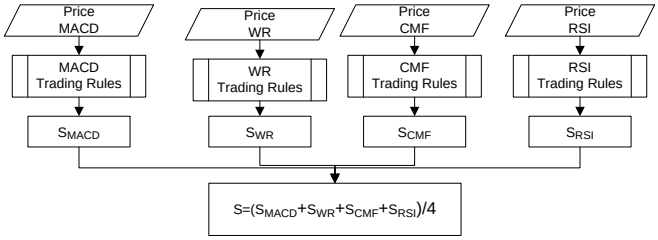
The flow chart of fuzzy logic function for MACD indicator is shown in Figure 25, and the combined signal is illustrated in Figure 26.

Figure 25: Fuzzy logic function-MACD




*Source: Deutsche Bank Quantitative Strategy*

Figure 26: Fuzzy logic functions and combined signal




*Source: Deutsche Bank Quantitative Strategy*

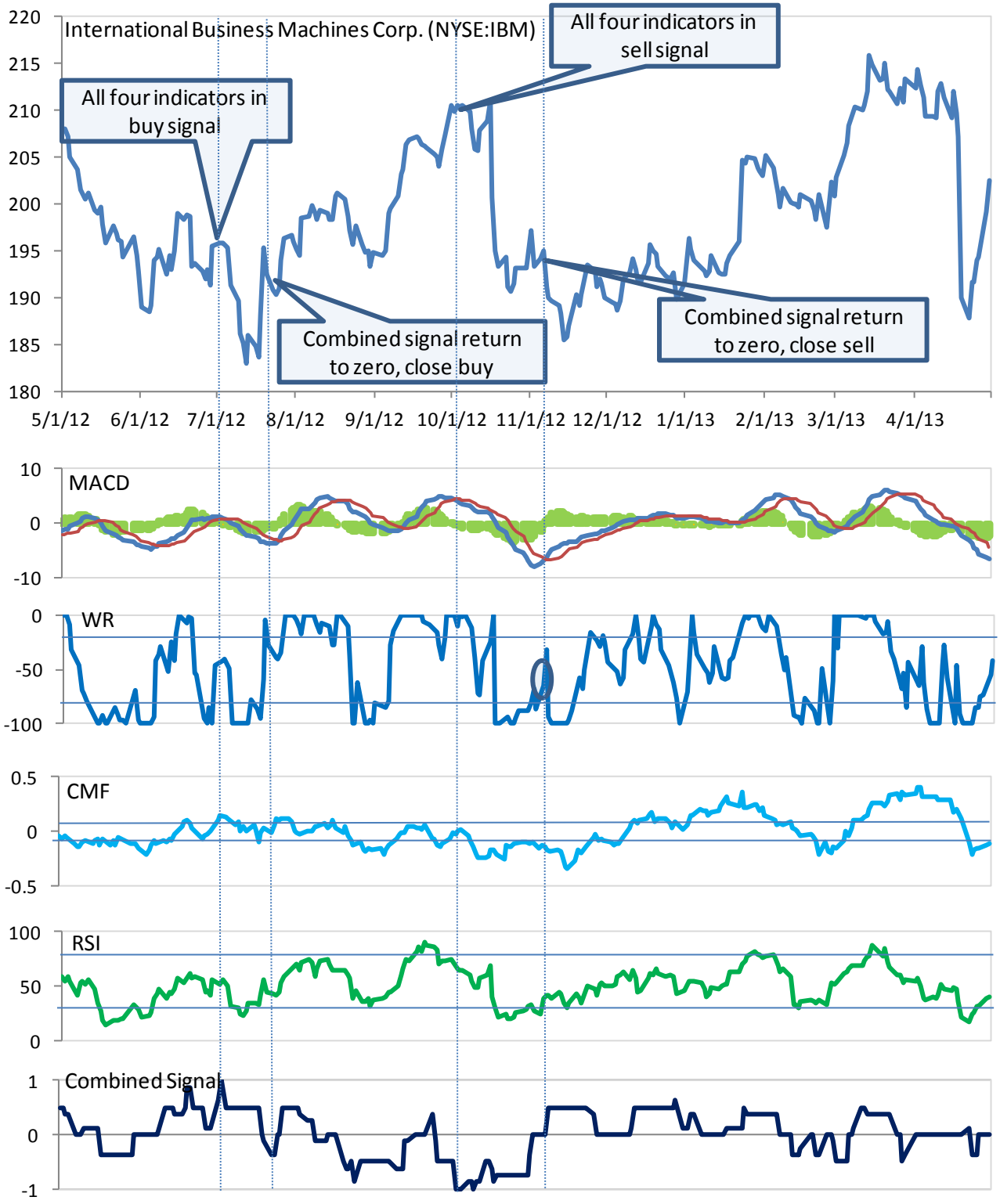
We denote $S_{MACD}$, $S_{WR}$, $S_{CMF}$, $S_{RSI}$ as the signal values from the fuzzy logic functions of MACD, William's %R, Chaikin Money Flow, and RSI respectively, and the comprehensive signal S is defined as the mean of $S_{MACD}$, $S_{WR}$, $S_{CMF}$, and $S_{RSI}$.

The trading rules here are:

- Buy if S=1,
- Close buy position if S drops below zero,
- Short if S=-1,
- Close short position if S increases above zero

Signal examples are shown in Figure 27.

Figure 27: Signals with four indicators




*Source: Deutsche Bank Quantitative Strategy*

We then re-run the backtesting with signals from this fuzzy logic function. Results are shown in Figure 28 and Figure 29. As expected, the return per trade on average has improved to 0.66%, from negative territory. The number of trades is also reduced

significantly since we only buy and sell when we have the conviction of four indicators pointing in the same direction.

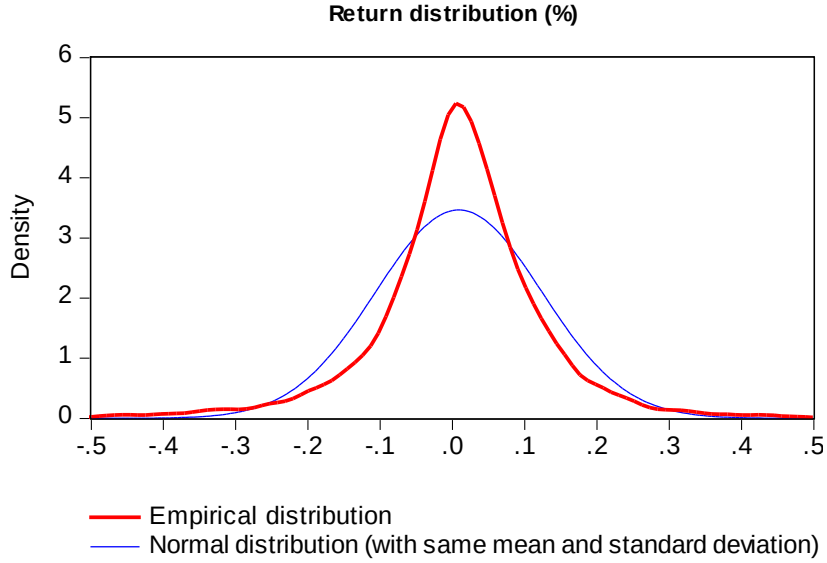
Figure 28: US Result Summary – Stone Age Combined Signals

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| Combined | Long | 6,774 | 1.73% | 34.3 | 0.050% | 59.6% | 0.38% |
| | Short | 5,238 | -0.71% | 32.3 | -0.022% | 49.5% | -1.44% |
| | **Total** | **12,012** | **0.66%** | **33.4** | **0.020%** | **55.2%** | **-0.41%** |

*Source: Deutsche Bank Quantitative Strategy*

The useful finding here is that the long signals generate 1.73% return per trade on average, and outperforms the S&P 500 Index by 0.38%. This also implies that in general the market timing long signals do predict the uptrend of the market successfully (the benchmark is up 1.4% on average). By contrast, the benchmark is up 0.7% on average during the short periods.

Figure 29: US Stone Age Combined Signals




*Source: Deutsche Bank Quantitative Strategy*

We test the global markets with the same fuzzy logic functions, and the results are similar. Figure 30 shows the results for the S&P BMI Japan Index universe.[9] Stock prices and returns are in local currency. As with the US market, the long side works better than the short side. We are making progress, but we still have a long way to go.

Figure 30: Japan Result Summary – Stone Age Combined Signals

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| Combined | Long | 25,314 | -0.80% | 41.4 | -0.019% | 47.3% | 0.02% |
| Combined | Short | 14,025 | -1.16% | 33.4 | -0.035% | 51.5% | -1.78% |
| | **Total** | **39,339** | **-0.93%** | **38.6** | **-0.024%** | **48.8%** | **-0.62%** |

*Source: Deutsche Bank Quantitative Strategy*

[9] Results for other markets available on request.

# The Bronze Age

## Market Timing Hypothesis I – Price Movement

Ancient people gradually learned how to melt bronze ore, and stone tools were replaced by bronze tools. The emergence of bronze tools improved the quality of life greatly, and accelerated the process of civilization. In our analogy, the Stone Age timing tools we studied in the previous section showed some promise, mainly on the long side. What new tools can we invent to move into the Bronze Age?

As we mention in the previous section, volatility indicators cannot tell us the direction of future price movement, and hence are excluded in our signal system. However, we do believe that volatility plays an important role in the market. Specifically, we hypothesize that we can use the volatility of a stock's price to determine whether a buy or sell signal from a technical rule is likely to be a real signal, or simply a false positive.

For example, suppose a stock has a volatility of $\sigma$ percent. Then we might plausibly argue that price movements within say, $\pm 2\sigma$ are "normal" and therefore not a strong directional signal. However, once a stock moves outside of that range, we sit up and take notice, because something is afoot. Therefore, we suggest a new rule where first we construct trading bands based on a stock's past volatility, and then we only act on buy signals when the price moves above the upper band. Similarly, we only act on sell signals when the price moves below the band. For both buy and sell signals that occur within the band, we ignore them as false signals. Another way to think about this is that we need *double* confirmation for a trade: for a buy we need (1) the stock to break out above the range, and (2) the technical rule indicates a buy. For a sell we need (1) the stock to break out below the range, and (2) the technical rule indicates a sell.

Mathematically, for a given stock we first calculate its 42-day trailing volatility, $\sigma_t$, based on daily price returns. We picked 42 days as a good balance between having enough data points to compute volatility accurately, but not so many that we have to look back too far into stale data. Additionally, if we think back to the Stone Age, the average holding period was around 35 days, so a rolling window of 42 days is a reasonable period to capture the volatility over the life of a particular trade.[10]

Since we need 42 days of data for the first volatility calculation, the algorithm starts at $t = 42$:

$$UB_t = \begin{cases} NA, t < 42 \\ P_t + 2\sigma_t, t = 42 \end{cases}$$

$$LB_t = \begin{cases} NA, t < 42 \\ P_t - 2\sigma_t, t = 42 \end{cases}$$

where $UB_t$ is the upper band value at time $t$, $LB_t$ is the lower band value at time $t$, and $\sigma_t$ is the rolling standard deviation of daily price returns of stock at time $t$, and $P_t$ is the stock price at time $t$. Then, in subsequent periods where $t > 42$:

[10] We also tried 63 and 90 days, and obtained qualitatively similar results.

$$UB_t = \begin{cases} UB_{t-1}, t > 42 \text{ and } UB_{t-1} > P_{t-1} > LB_{t-1} \\ P_{t-1} + 2\sigma_{t-1}, t > 42 \text{ and } P_{t-1} > UB_{t-1} \text{ and in buy signal} \\ P_{t-1} + 2\sigma_{t-1}, t > 42 \text{ and } P_{t-1} < LB_{t-1} \text{ and in sell signal} \end{cases}$$

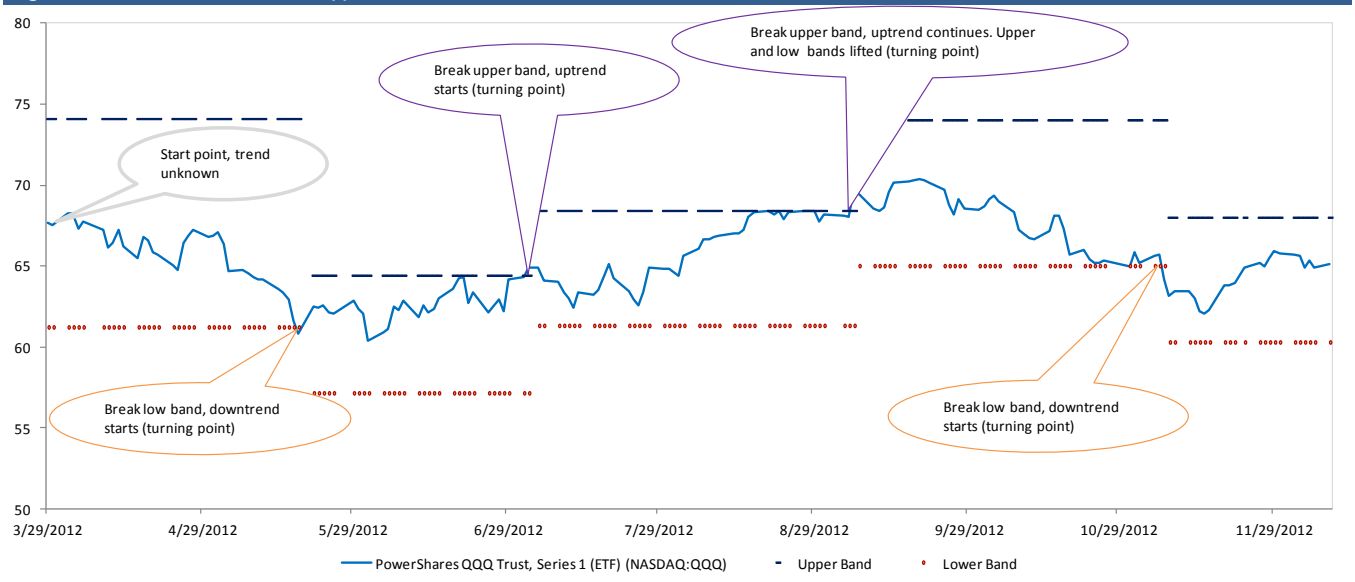
$$LB_t = \begin{cases} LB_{t-1}, t > 42 \text{ and } UB_{t-1} > P_{t-1} > LB_{t-1} \\ P_{t-1} - 2\sigma_{t-1}, t > 42 \text{ and } P_{t-1} > UB_{t-1} \text{ and in buy signal} \\ P_{t-1} - 2\sigma_{t-1}, t > 42 \text{ and } P_{t-1} < LB_{t-1} \text{ and in sell signal} \end{cases}$$

In other words, the bands are reset whenever the price breaks above (below) the upper (lower) band *and* the technical rule gives a buy (sell) signal.

Figure 31 shows the first part of the process – the bands themselves – before we overlay the technical trading rule. The bands have a dual function:

- **Directional function.** When the price breaks above the upper band, one short-term up trend is established. Similarly, when the price breaks below the lower band, the price is likely to continue to move lower.
- **Filter function.** When the price is within the range of the lower band and upper band, the trend is unchanged and thus any buy or sell signals will be discarded.

Figure 31: Price movement hypothesis

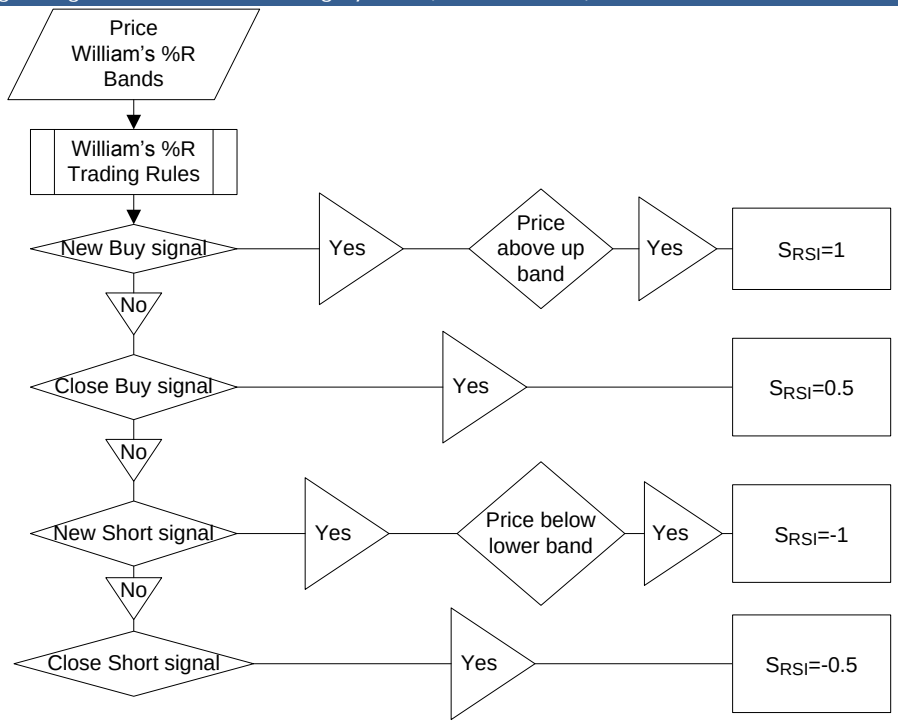



*Source: Deutsche Bank Quantitative Strategy*

## Adding in the technical rule

Next, we combine the bands with the fuzzy logic function shown in Figure 32, in this case using William's %R as an example rule. Again, the key point is that signals from the W%R rule are ignored, unless the stock has broken outside the volatility-defined trading range.

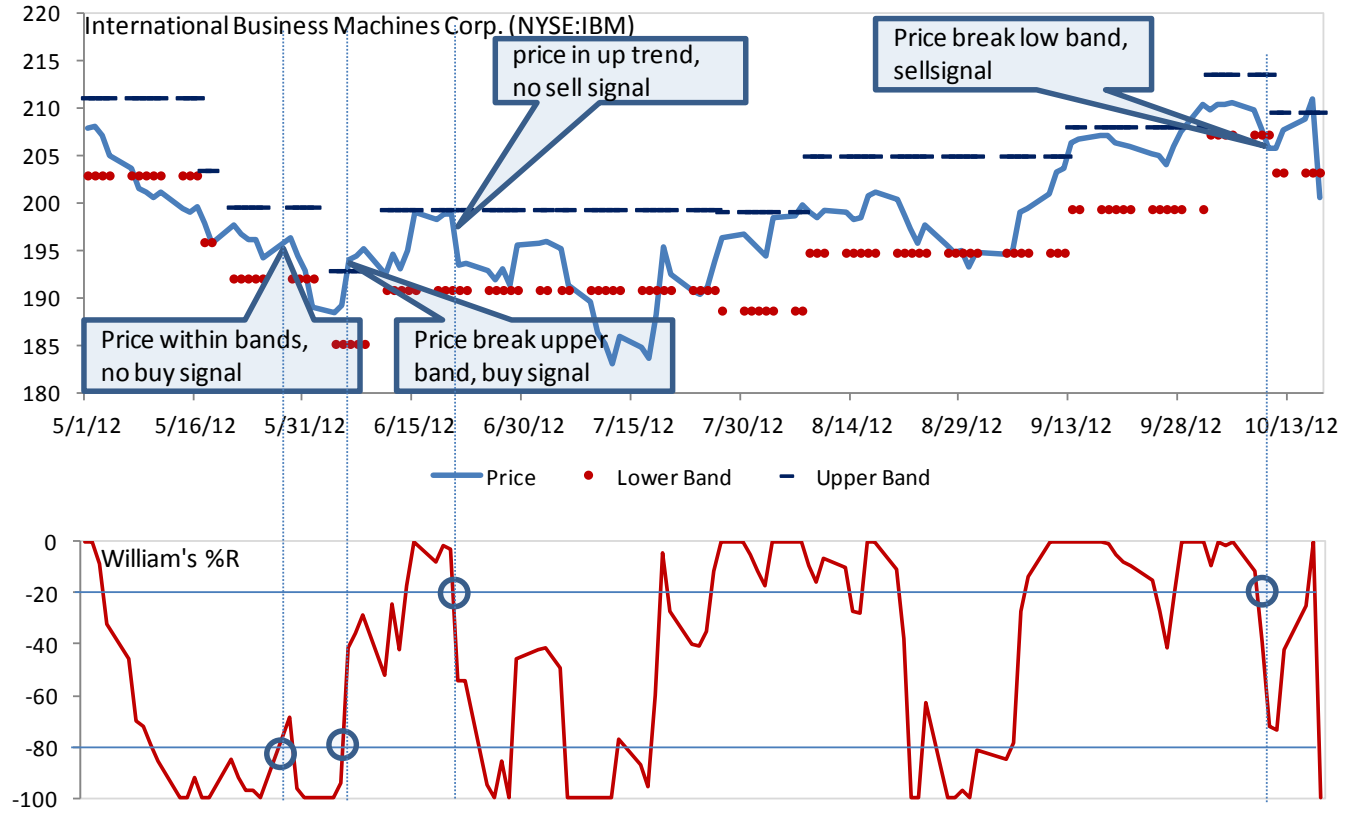
Figure 32: Bronze Age - logic function and trading system (William's %R)




*Source: Deutsche Bank Quantitative Strategy*

A single stock example of the mechanism in action is shown in Figure 33.

Figure 33: Bronze Age example




Source: Deutsche Bank Quantitative Strategy

## Performance metrics

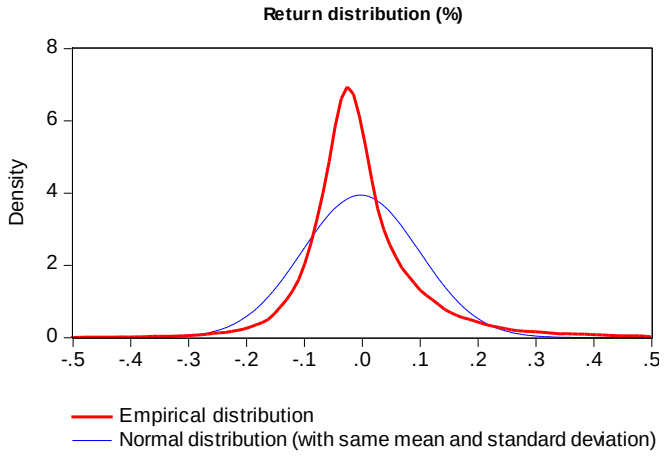
We re-run our performance tests with the new signal system, and expect better performance and less trades. Testing results are shown in Figure 34 to Figure 38.

Figure 34: US Result Summary – Bronze Age Individual Indicator Signals

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| MACD | Long | 36,326 | 0.87% | 26.6 | 0.033% | 43.7% | 0.10% |
| | Short | 30,777 | -0.92% | 22.0 | -0.042% | 35.3% | -1.64% |
| | **Total** | **67,103** | **0.04%** | **24.5** | **0.002%** | **39.8%** | **-0.69%** |
| WR | Long | 47,693 | 0.42% | 9.2 | 0.046% | 57.7% | 0.12% |
| | Short | 34,070 | -0.37% | 10.5 | -0.035% | 52.7% | -0.66% |
| | **Total** | **81,763** | **0.09%** | **9.7** | **0.009%** | **55.6%** | **-0.20%** |
| CMF | Long | 43,504 | 0.67% | 22.3 | 0.030% | 46.6% | 0.16% |
| | Short | 36,093 | -0.76% | 17.1 | -0.045% | 39.6% | -1.44% |
| | **Total** | **79,597** | **0.02%** | **19.9** | **0.001%** | **43.4%** | **-0.56%** |
| RSI | Long | 12,690 | 1.86% | 42.5 | 0.044% | 71.0% | 0.24% |
| | Short | 9,682 | -1.89% | 49.3 | -0.038% | 59.9% | -3.25% |
| | **total** | **22,372** | **0.24%** | **45.4** | **0.005%** | **66.2%** | **-1.27%** |

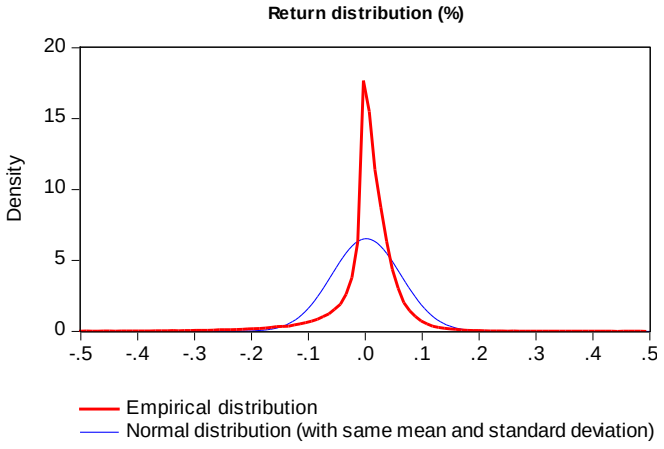
Source: Deutsche Bank Quantitative Strategy

## Figure 35: US Bronze Age MACD Signals



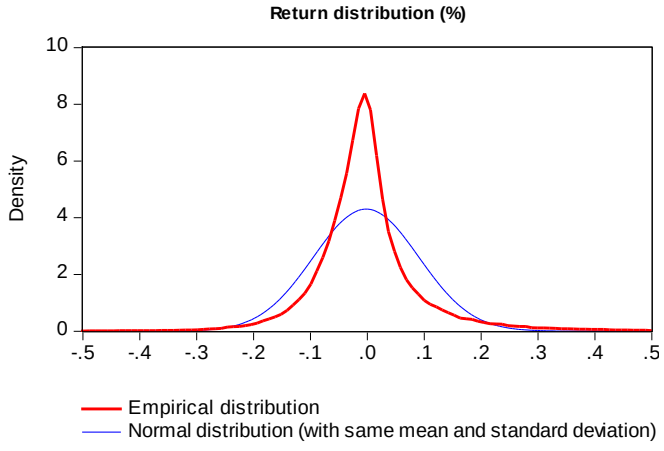

*Source: Deutsche Bank Quantitative Strategy*

## Figure 36: US Bronze Age WR signals



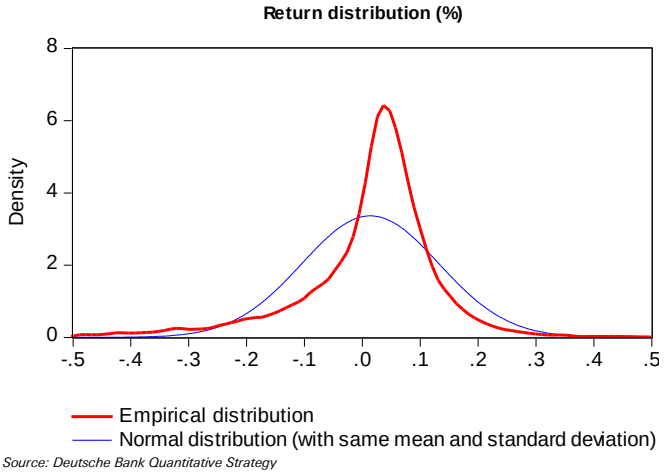

*Source: Deutsche Bank Quantitative Strategy*

## Figure 37: US Bronze Age CMF Signals




*Source: Deutsche Bank Quantitative Strategy*

## Figure 38: US Bronze Age RSI Signals




*Source: Deutsche Bank Quantitative Strategy*

We can see some improvement in the tests of individual indicators when compared to the Stone Age signals (i.e. the same trading rules, but without the trading range bands). The results for S&P BMI Japan Index universe also suggest the trading system in the Bronze Age is better than that of the Stone Age. Results for other markets are available on request.

Figure 39: Japan Result Summary – Bronze Age Individual Indicator Signals

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| MACD | Long | 98,354 | 0.21% | 24.1 | 0.009% | 36.9% | 0.27% |
| | Short | 95,174 | 0.03% | 23.9 | 0.001% | 40.2% | 0.10% |
| | **Total** | **193,528** | **0.12%** | **24.0** | **0.005%** | **38.5%** | **0.19%** |
| WR | Long | 112,431 | -0.09% | 10.4 | -0.009% | 48.6% | -0.11% |
| | Short | 114,223 | -0.05% | 9.1 | -0.005% | 52.1% | 0.01% |
| | **Total** | **226,654** | **-0.07%** | **9.7** | **-0.007%** | **50.3%** | **-0.05%** |
| CMF | Long | 103,654 | 0.06% | 20.5 | 0.003% | 41.9% | 0.20% |
| | Short | 99,445 | -0.24% | 20.2 | -0.012% | 44.1% | -0.30% |
| | **Total** | **203,099** | **-0.08%** | **20.4** | **-0.004%** | **43.0%** | **-0.05%** |
| RSI | Long | 28,002 | 0.10% | 69.3 | 0.001% | 59.7% | 0.17% |
| | Short | 27,218 | -0.16% | 41.6 | -0.004% | 63.6% | -0.16% |
| | **total** | **55,220** | **-0.03%** | **55.6** | **0.000%** | **61.6%** | **0.01%** |

*Source: Deutsche Bank Quantitative Strategy*

Next we test the aggregate signal based on the four rules combined together, along with the upper band and low band criteria:

- Buy if S=1,
- Close buy position if S drops below zero,
- Short if S=-1,
- Close short position if S increases above zero

Figure 40: US Result Summary – Bronze Age Combined Signals

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| Combined | Long | 983 | 3.10% | 82.4 | 0.038% | 46.2% | 0.63% |
| | Short | 305 | -4.10% | 53.3 | -0.077% | 33.4% | -6.00% |
| | **Total** | **1,288** | **1.40%** | **75.5** | **0.018%** | **43.2%** | **-0.94%** |

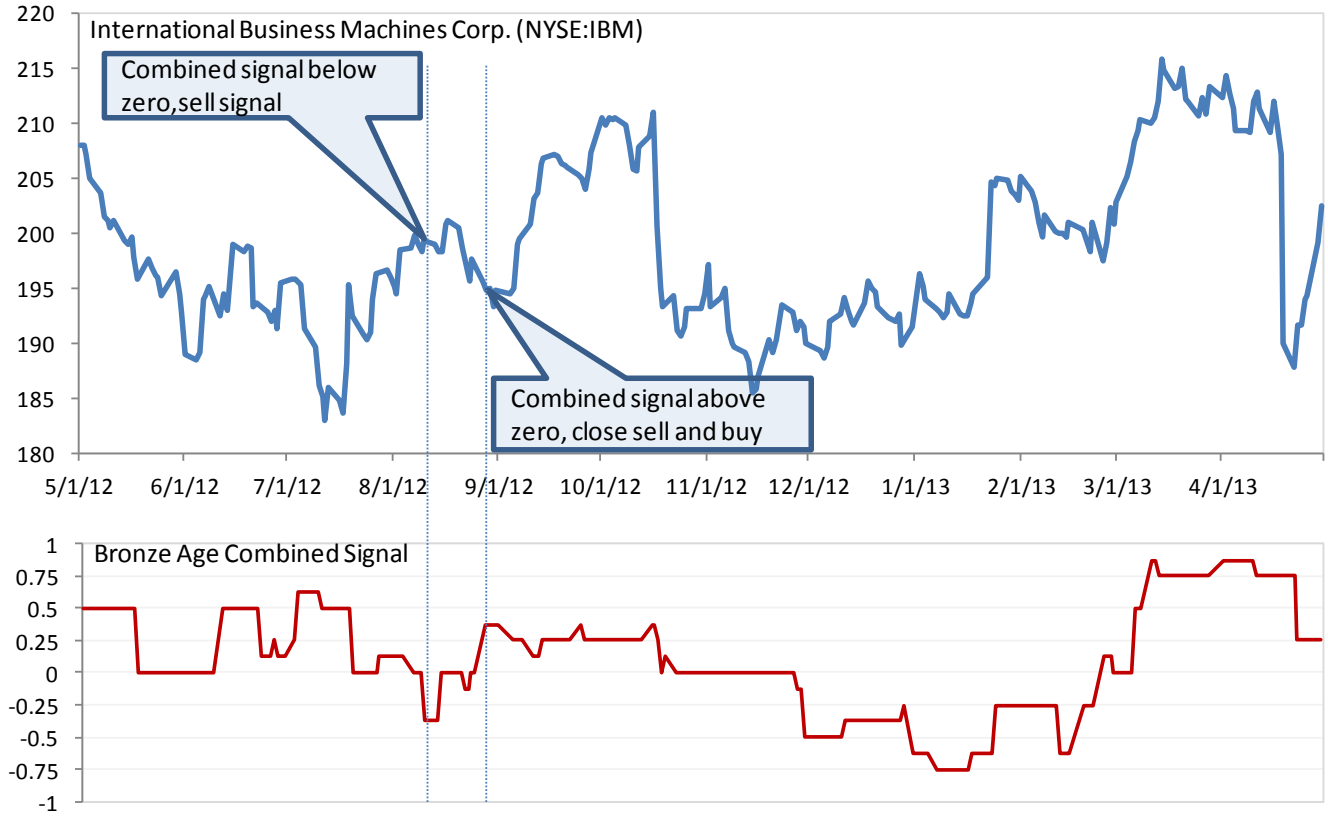
*Source: Deutsche Bank Quantitative Strategy*

There are only 1,288 trades during the test period (or roughly 6 trades per month), which suggests that the trading rules are too strict. Therefore we relax the constraints on the combined signals with following trading rules:

- Buy if S=0.25,
- Close buy position if S drops below zero,
- Short if S=-0.25,
- Close short position if S increases above zero

An example of this rule is illustrated in Figure 41.

Figure 41: Signal Example – Bronze Age Combined Signal




Source: Deutsche Bank Quantitative Strategy

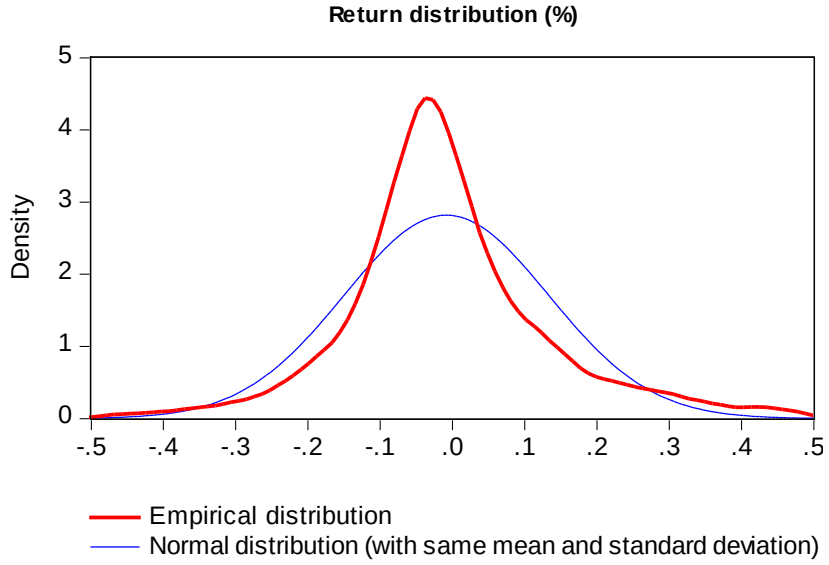
The results in Figure 42 show improvement from the Stone Age in terms of excess return. For example, in the US market the average return per trade on the long side is 2.44%, compared to 1.74% for the Stone Age rules. However, the short side still generates losses. As well, a lot of the improvement in average return is due to the fact the holding period is, on average, around double the Stone Age holding period (see Figure 28). So this evolutionary step shows some fledging signs of promise, but there's a long way to go yet.

Figure 42: US Result Summary – Bronze Age Combined Signals – Less Constraints

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| Combined | Long | 9,736 | 2.44% | 75.4 | 0.032% | 45.9% | 0.36% |
| | Short | 6,152 | -2.49% | 51.1 | -0.049% | 35.3% | -0.95% |
| | **Total** | **15,888** | **0.53%** | **66.0** | **0.008%** | **41.8%** | **-0.15%** |

Source: Deutsche Bank Quantitative Strategy

Figure 43: US Bronze Age Combined Signals




*Source: Deutsche Bank*

Looking at other markets, the performance of combined signals in the S&P BMI Japan Index universe is better – both long side and short side work. Again, results for other countries are available on request.

Figure 44: Japan Result Summary – Bronze Age Combined Signals – Less Constraints

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| Combined | Long | 56,934 | 0.19% | 51.9 | 0.004% | 37.6% | 0.19% |
| | Short | 55,601 | 0.07% | 45.3 | 0.001% | 42.3% | 0.27% |
| | **Total** | **112,535** | **0.13%** | **48.6** | **0.003%** | **39.9%** | **0.23%** |

*Source: Deutsche Bank Quantitative Strategy*

# The Iron Age

## Market Timing Hypothesis II – Size Effect

The discovery of iron brought people more robust tools to make life much easier in ancient society. The dark metal has remained an essential element since it was first forged.

So far we haven't used market conditions in our trading system. In other words, we apply the same trading rules regardless of whether we are in a bull market or a bear market. Perhaps we can do better by taking into account prevailing market conditions?

But how can we determine what type of market we are in? One simple observation is that in a bull market small cap stocks tend to outperform large cap stocks, while during the bear markets, the small cap stocks drop faster than the large cap stocks. This phenomenon leads to the hypothesis that at turning points where large cap stocks begin to outpace small cap stocks, the market is entering a bear market, and vise versa.

We define the spread between small cap stocks and large cap stocks as

$$SPRD_t = \log\frac{PS_t}{PL_t}$$

where $SPRD_t$ is the spread at time $t$, $PS_t$ is the small cap index level at time $t$, and $PL_t$ is the large cap index level at time $t$. The deviation of the spread is calculated as following:

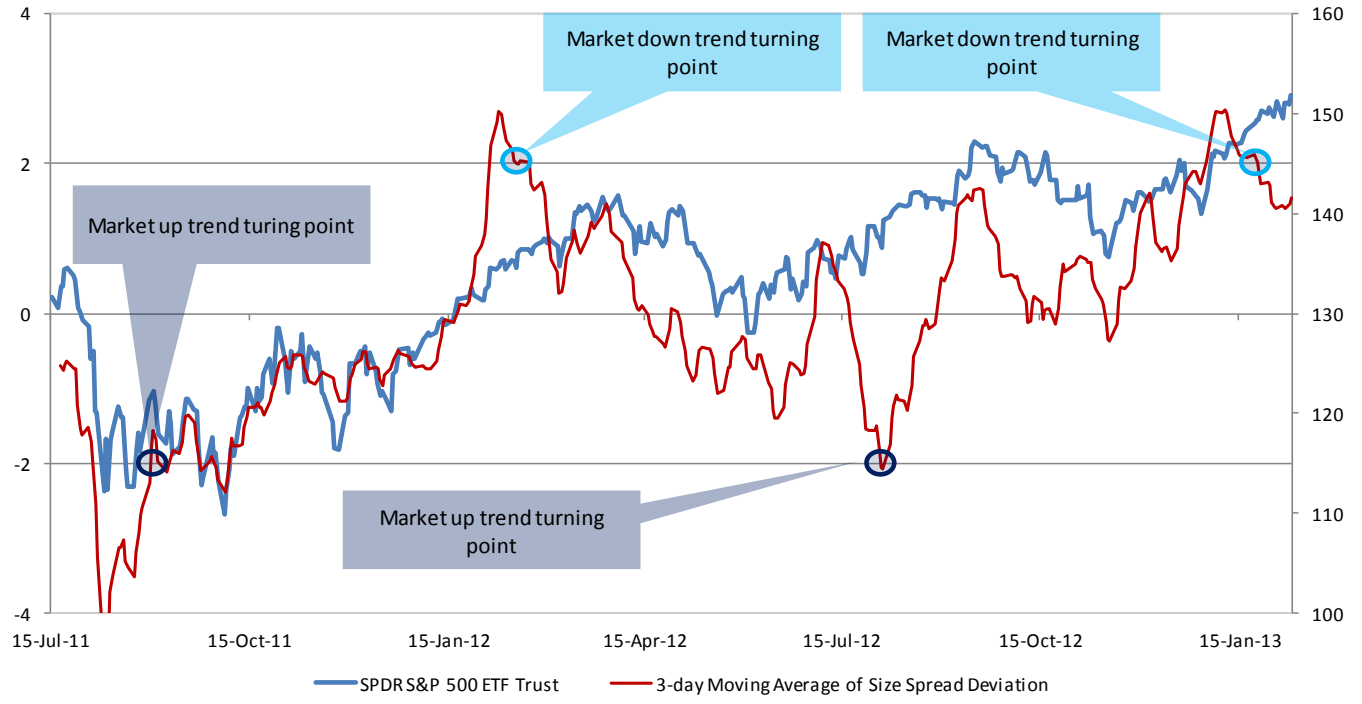
$$\overline{SPRD_t} = \frac{1}{N}\sum_{i=t-(N-1)}^{t} SPRD_i$$

$$\sigma_t = \sqrt{\frac{1}{N-1}\sum_{i=t-(N-1)}^{t}(SPRD_i - \overline{SPRD_i})^2}$$

$$D_t = \frac{SPRD_t - \overline{SPRD_t}}{\sigma_t}$$

where $N$=130, $DT_t$ is the number of standard deviations the current spread is away from its 130-day moving average at time $t$, measured in terms of the 130-day rolling standard deviation ($\sigma_t$). The relationship between the spread deviation and the market is illustrated in Figure 45. We use 3-day moving average of $D_t$ to smooth the line.

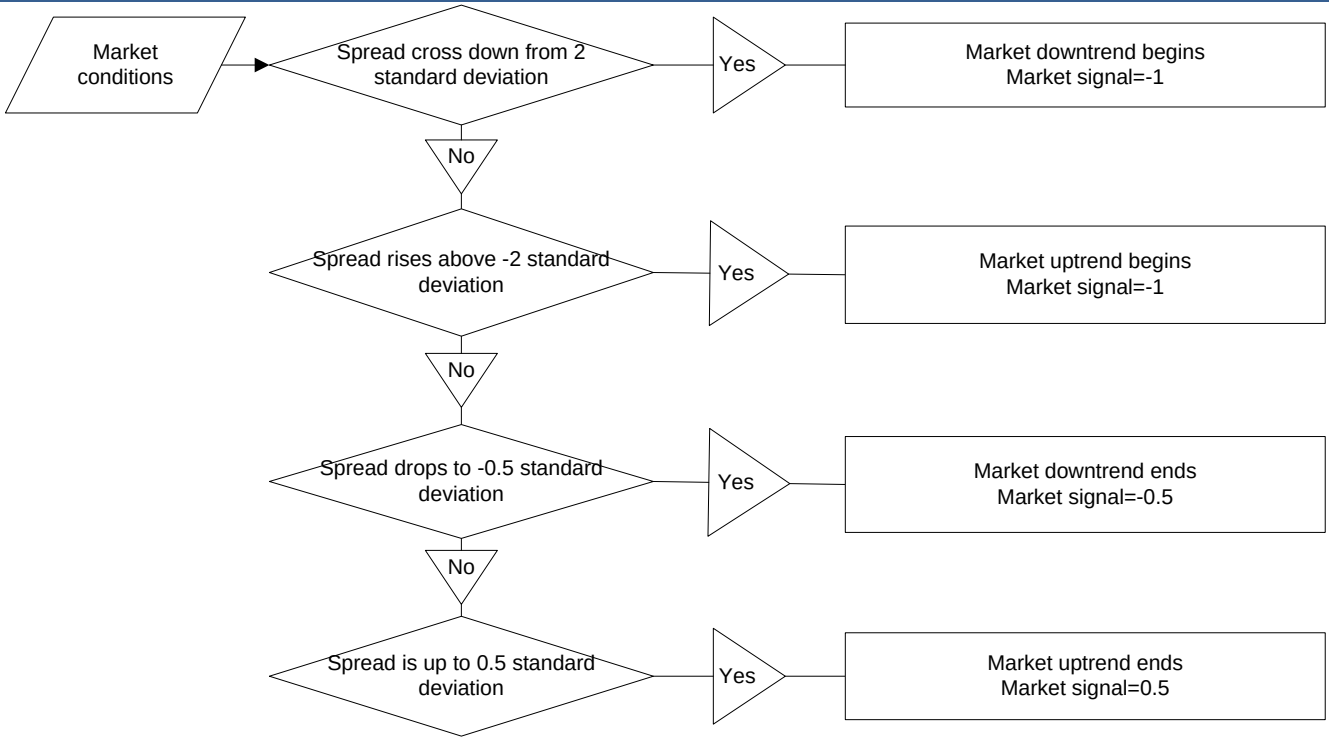
Figure 45: Market and the size effect




*Source: Deutsche Bank Quantitative Strategy*

The turning points are when $D_t$ crosses from below -2 to above -2 or when it crosses from above 2 to below 2. We can design market signals based on this assumption, as shown in Figure 46.

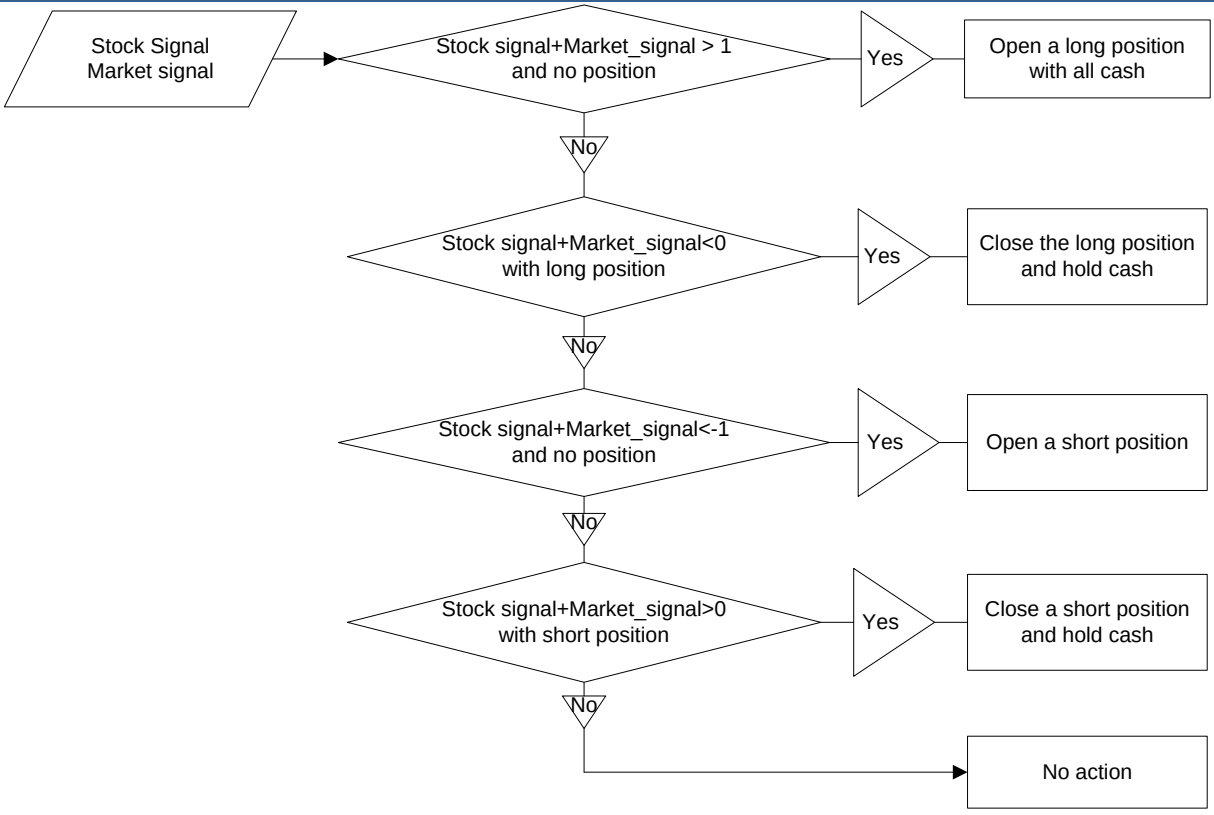
Figure 46: Iron Age – Market Signals




*Source: Deutsche Bank Quantitative Strategy*

We then combine signals from Figure 32 with market signals, resulting in our Iron Age trading system, as shown in Figure 47.

Figure 47: Iron Age – Signal System

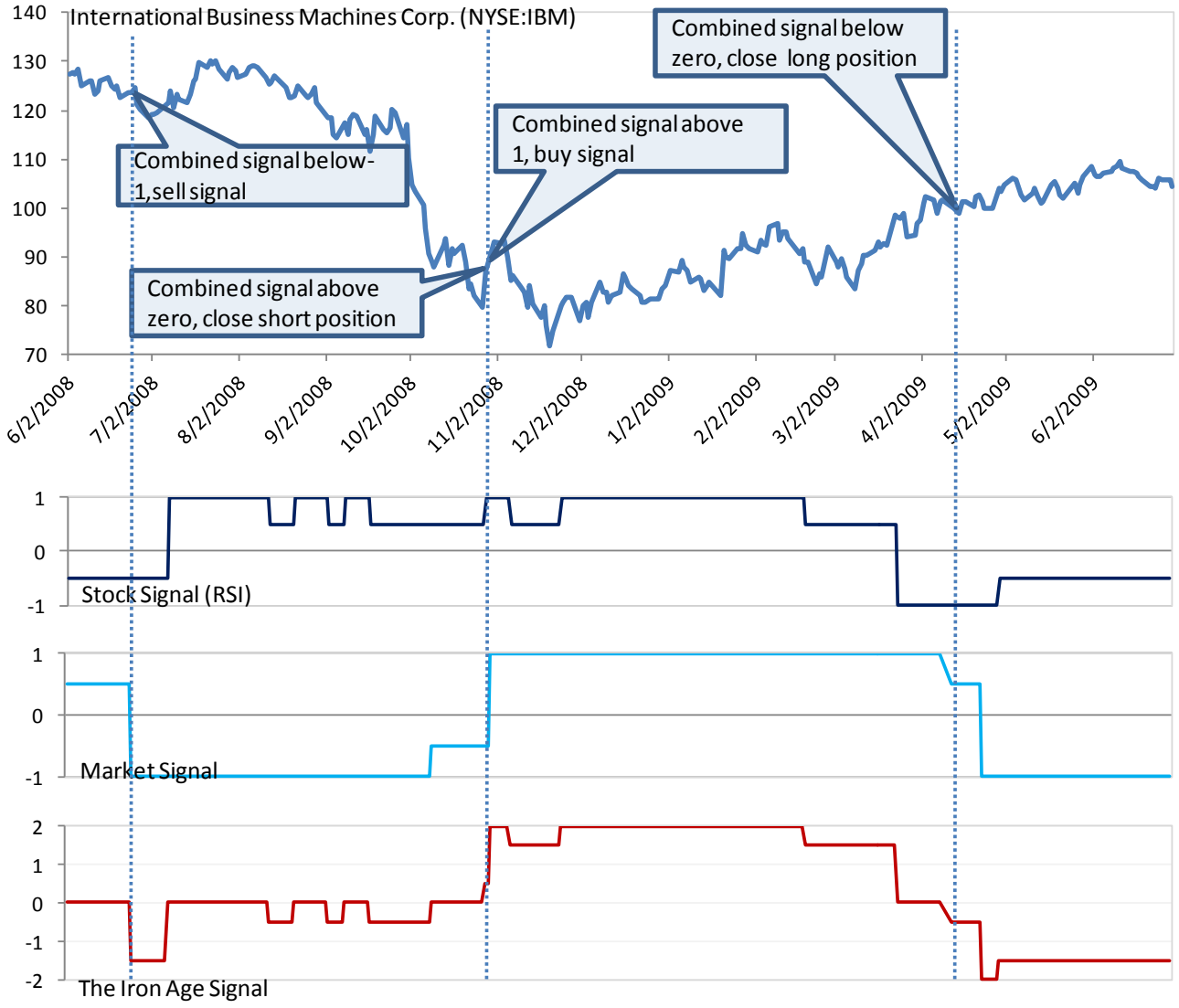



*Source: Deutsche Bank Quantitative Strategy*

As before, the rules used in the system can either be a single rule (e.g. RSI, W%R) or the composite of the four rules. Note that each rule incorporates the trading bands developed in the Bronze Age, i.e. the "stock signal" denotes the combination of a rule plus the trading band.

Figure 48 shows an example for a single stock using the RSI rule.

Figure 48: Iron Age Signal Example




*Source: Deutsche Bank Quantitative Strategy*

## Performance metrics

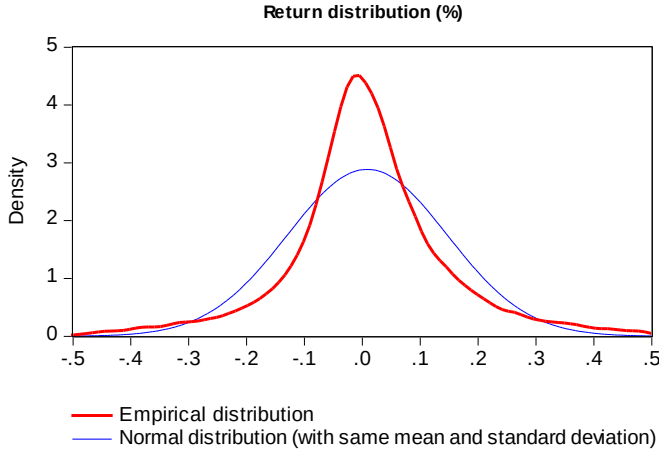
We test the new trading system once again in the S&P 500. Backtesting results are shown in Figure 49 to Figure 55. The Iron Age signal system performs consistently across all indicators. On average, the Buy signals generate about 12% on an annual basis for individual indicators, and 13% for the combined signals. However, in all cases, the Sell signals fail to deliver positive results and also underperform the benchmark.

Figure 49: US Result Summary – Iron Age Individual Indicator Signals

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| MACD | Long | 13,467 | 3.23% | 68.7 | 0.047% | 60.2% | 0.32% |
| | Short | 15,998 | -0.63% | 54.7 | -0.011% | 43.7% | -0.95% |
| | **Total** | **29,465** | **1.13%** | **61.1** | **0.019%** | **51.2%** | **-0.37%** |
| WR | Long | 10,440 | 4.68% | 102.0 | 0.046% | 60.0% | 0.68% |
| | Short | 10,096 | -0.46% | 46.4 | -0.010% | 41.3% | -0.90% |
| | **Total** | **20,536** | **2.16%** | **74.7** | **0.029%** | **50.8%** | **-0.10%** |
| CMF | Long | 9,539 | 4.62% | 97.7 | 0.047% | 55.1% | 0.84% |
| | Short | 10,489 | -0.34% | 64.9 | -0.005% | 41.0% | -0.74% |
| | **Total** | **20,028** | **2.02%** | **80.5** | **0.025%** | **47.7%** | **0.01%** |
| RSI | Long | 6,847 | 5.77% | 114.9 | 0.050% | 64.9% | 0.80% |
| | Short | 7,258 | -1.50% | 99.7 | -0.015% | 47.9% | -2.69% |
| | **total** | **14,105** | **2.03%** | **107.1** | **0.019%** | **56.2%** | **-1.00%** |

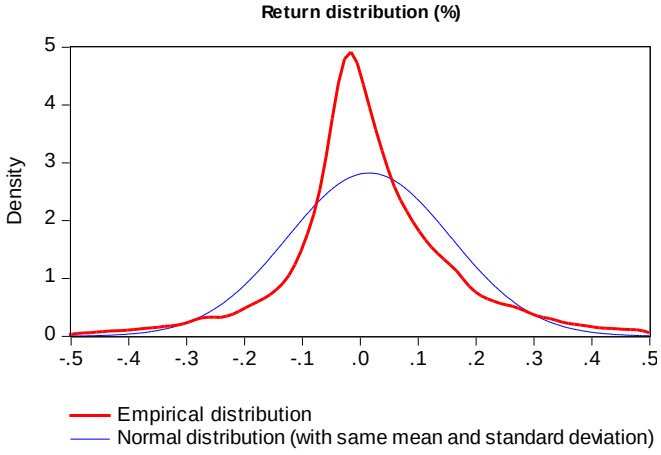
*Source: Deutsche Bank Quantitative Strategy*

Figure 50: US Iron Age – MACD Signals



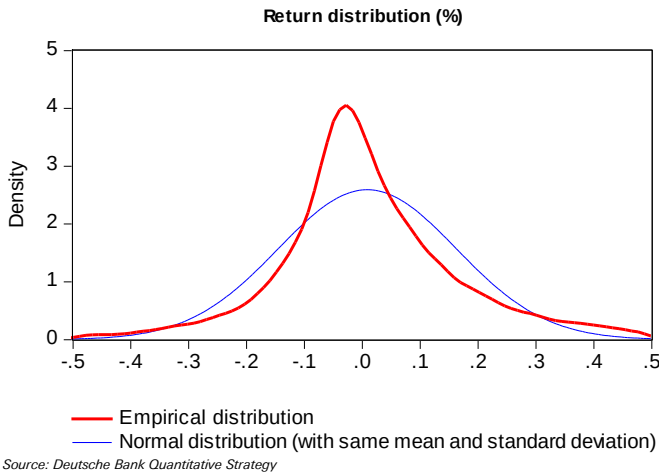

*Source: Deutsche Bank Quantitative Strategy*

Figure 51: US Iron Age – WR Signals



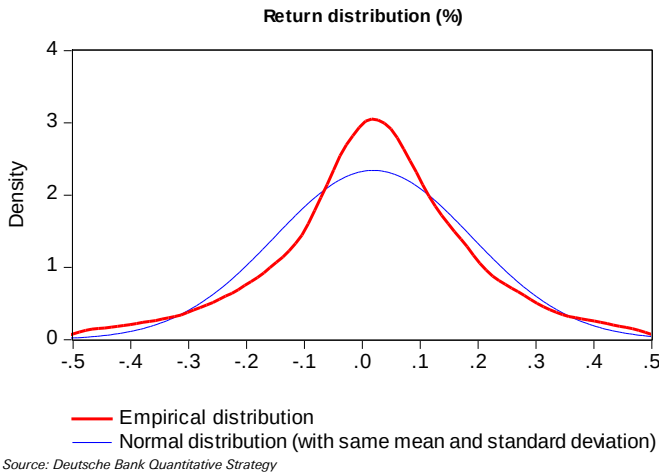

*Source: Deutsche Bank Quantitative Strategy*

Figure 52: USIron Age – CMF Signals




Source: Deutsche Bank Quantitative Strategy

Figure 53: US Iron Age – RSI Signals



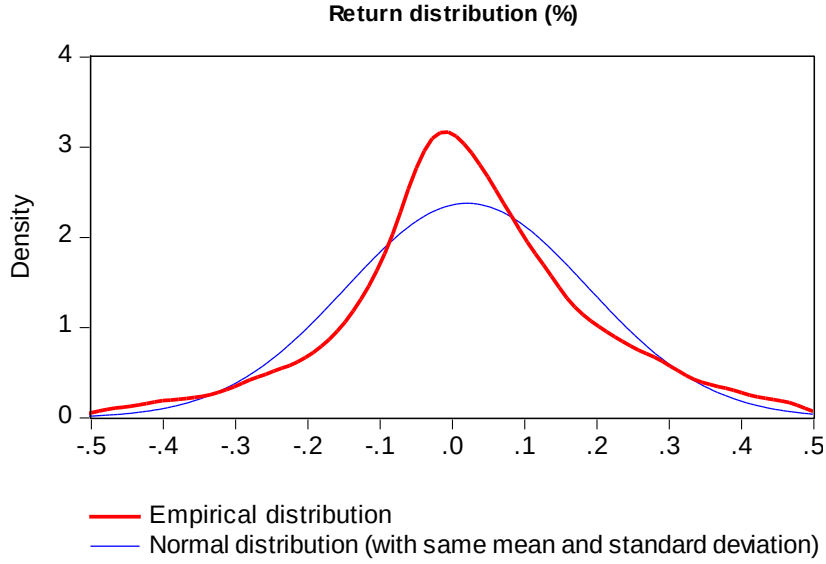

Source: Deutsche Bank Quantitative Strategy

Figure 54: US Result Summary – Iron Age Combined Signals

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| Combined | Long | 8,086 | 6.44% | 125.5 | 0.051% | 62.8% | 1.27% |
| | Short | 8,065 | -0.11% | 75.2 | -0.001% | 45.9% | -0.19% |
| | **Total** | **16,151** | **3.17%** | **100.4** | **0.032%** | **54.3%** | **0.54%** |

Source: Deutsche Bank Quantitative Strategy

Figure 55: US Iron Age Combined Signals




Source: Deutsche Bank

At first glance, the market timing ability seems weak even with the combined signals. However, a closer examination of the results reveals a bright spot. Over all trades, the S&P 500 Index was up 10% annually when stocks were held long, while the market was flat (0.3%) during periods where stocks were held short. This finding suggests that the combined signals in the Iron Age do have strong market timing ability.

Implementing the Iron Age trading system in a global universe requires extra work. The hurdle is that not every market has a well established large cap index and small cap index. However, we can construct the two indexes from the stocks in the universe based on company size.

The first step of the index construction is to rank stocks in the universe by their market capitalization from large to small at each point in time. We pick the top 10% of ranked stocks as large cap stocks and calculate the mean of their daily returns as daily returns for the large cap index. As a general rule, the number of small cap stocks in an index is far more than the number of large cap stocks. We pick stocks that are ranked in the bottom 60% as small cap stocks and calculate daily returns of the small cap index in same way as the large cap index. Then the index values can be calculated from the daily returns with a base 100 at the first data point.

Figure 56 shows the backtesting results in S&P BMI Japan Index universe. All stock prices and returns are in local currency (Yen). The Japanese equity market was mainly in downtrend during the backtesting period, and therefore the short signals work better than the long signals.

Figure 56: Japan Result Summary – Iron Age Signals

| Indicator | Signal Type | # of Trades | Average Return | Average Holding Days | Average Daily Return | Winning Ratio | Excess Return |
|---|---|---|---|---|---|---|---|
| MACD | Long | 29,504 | -0.40% | 127.0 | -0.003% | 52.4% | 1.02% |
| | Short | 19,720 | 2.27% | 79.4 | 0.029% | 55.8% | 3.61% |
| | **Total** | **49,224** | **0.67%** | **107.9** | **0.006%** | **53.7%** | **2.05%** |
| WR | Long | 23,183 | 0.01% | 177.2 | 0.000% | 52.2% | 1.30% |
| | Short | 13,239 | 2.16% | 74.4 | 0.029% | 53.7% | 3.43% |
| | **Total** | **36,422** | **0.79%** | **139.8** | **0.006%** | **52.8%** | **2.07%** |
| CMF | Long | 17,369 | -0.26% | 195.5 | -0.001% | 47.6% | 1.04% |
| | Short | 13,267 | 1.46% | 98.7 | 0.015% | 51.9% | 2.72% |
| | **Total** | **30,636** | **0.49%** | **153.6** | **0.003%** | **49.5%** | **1.77%** |
| RSI | Long | 13,624 | -1.58% | 267.4 | -0.006% | 53.0% | 1.32% |
| | Short | 8,262 | 3.65% | 118.5 | 0.031% | 63.1% | 5.94% |
| | **total** | **21,886** | **0.39%** | **211.2** | **0.002%** | **56.8%** | **3.06%** |
| Combined | Long | 13,716 | 0.08% | 297.7 | 0.000% | 51.3% | 1.39% |
| | Short | 11,131 | 3.17% | 107.3 | 0.030% | 58.5% | 4.88% |
| | **Total** | **24,847** | **1.46%** | **212.4** | **0.007%** | **54.5%** | **2.95%** |

*Source: Deutsche Bank Quantitative Strategy*

# The Modern Age

## Bridging technical analysis and quantitative research

People in the Iron Age were limited in the distance they could travel. This led to a civilization that was largely dependent on local resources. But then a series of discoveries and innovation in the fields of science, politics, and technology in the late Iron Age transformed society and brought people into the Modern Age. New technologies were adopted in transportation, which enabled people to reach areas that their ancestors could not imagine. Different cultures and isolated villages are connected.

Yes, we are stretching the analogy a little, but the combination of a technical trading system and traditional cross-sectional quantitative analysis offers new opportunities too. As we discussed in the introduction, technical analysis is different from quantitative research in the way the data is processed. Technical analysis rely on the pattern of historical individual time-series to predict the future, while strategists in the quantitative research world compare stocks cross-sectionally at each point in time to forecast future returns.

The first brick for building a bridge over the river between the technical analysis and quantitative research is a method for converting technical signals to cross-sectional alphas. We propose a factor called trading momentum (WIN) defined as following:

$$RT_{i,t} = \sum_{k=1}^{5} \left| r_{i,k} \right|$$

$$RP_{i,t} = \sum_{k=1}^{p} r_{i,k}, r_{i,k} > 0, p \le 5$$

$$WIN_{i,t} = \frac{RP_{i,t}}{RT_{i,t}}$$

where $RT_{i,t}$ is the sum of absolute returns for the most recent five trades of stock $i$ at time $t$, $RP_{i,t}$ is the sum of positive returns in most recent five trades of stock $i$ at time $t$, and $WIN_{i,t}$ is the trading momentum factor of stock $i$ at time $t$.

The rationale of the trading momentum factor is that we want to apply our technical system only to stocks where the rules have been working. Across all stocks in a market at any point in time, some stocks will be more conducive to a particular rule than others. Therefore, our momentum signal assumes that there will be some persistence in the ability of a rule to correctly time a stock in the future.

Recall that the average holding period of the combined signals is about 100 business days, so the five most recent trades contains about two years of trading information.

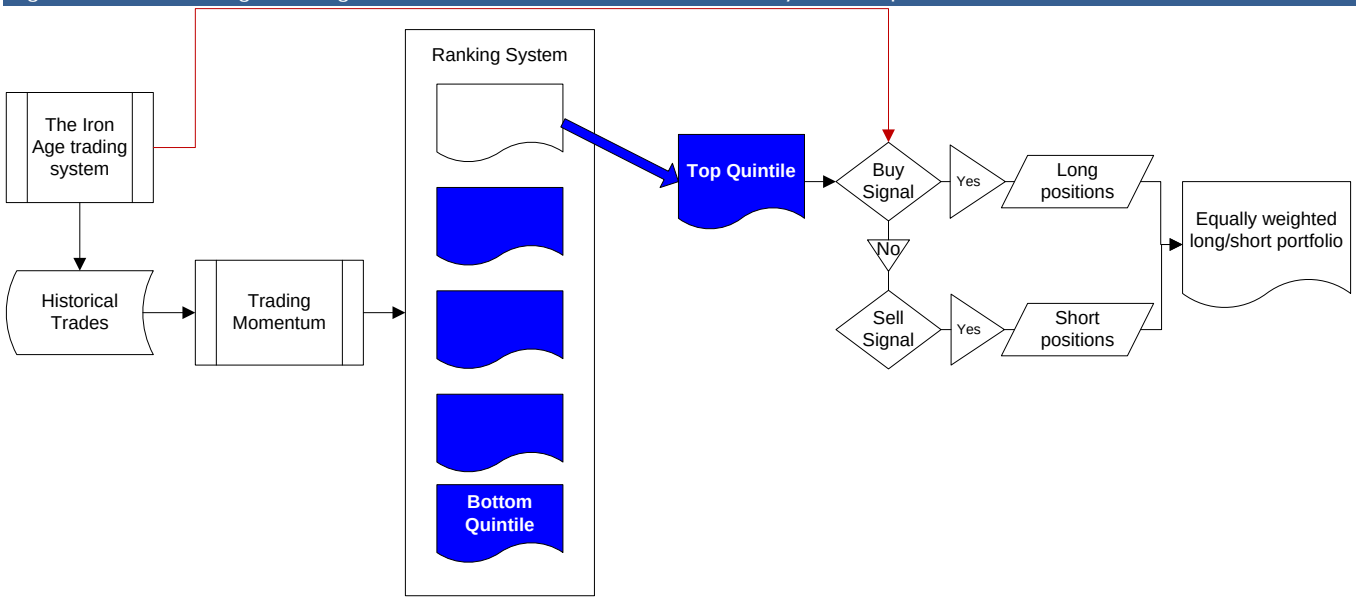
The next step is to set up a ranking system based on the trading momentum factor. At each point in time, we rank stocks in the universe based on the trading momentum factor from high to low, then we select the top quintile stocks as investment candidates for the next holding period, which we will set as one month.

The last phase of the bridge's construction is to bring in the market timing signals. Recall that at each point in time, every stock in the universe has a trading signal that

consists of a stock signal and a market signal. Stocks in the top quintile of trading momentum that also have buy signals will trigger long positions, while those in the top quintile of trading momentum that have sell signals will trigger short positions.

The whole process is illustrated in Figure 57.

Figure 57: Modern Age – Bridge over the river between technical analysis and quantitative research




*Source: Deutsche Bank Quantitative Strategy*

## Performance metrics

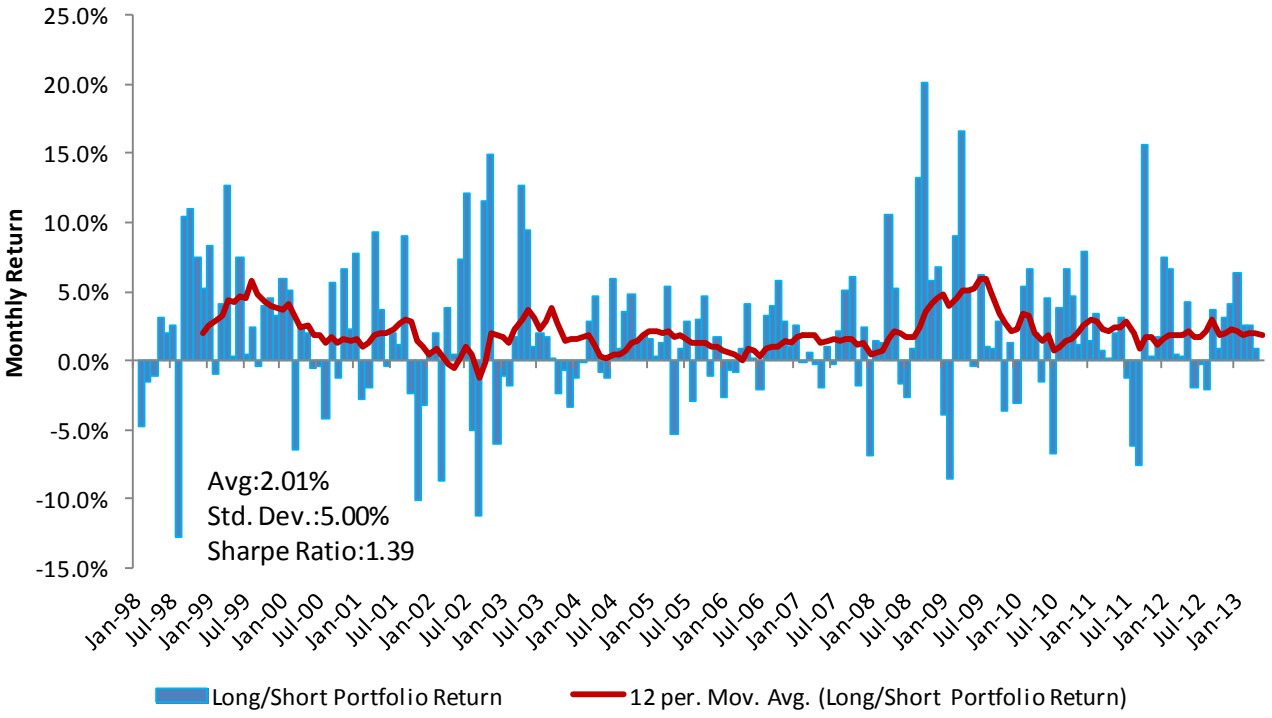
To test the new system, we need to use a quantitative backtesting methodology, instead of applying rules to individual stocks. Each month we go long the stocks that score above zero on their stock plus market signal, and short stocks that score below zero. Portfolios are held for one month and then rebalanced. We run this testing from January 1998 to April 2013, and produce the results in Figure 58 - Figure 60.

Figure 58: Market Timing Quantitative Portfolio – Summary

| | S&P 500 Index | Long Position | Short Position | Portfolio |
|---|---|---|---|---|
| Avg Monthly Return | 0.34% | 1.59% | 0.42% | 2.01% |
| Monthly Volatility | 4.66% | 4.28% | 3.35% | 5.00% |
| Sharpe Ratio | 0.25 | 1.29 | 0.43 | 1.39 |
| Avg number stocks | | 39 | 28 | 67 |

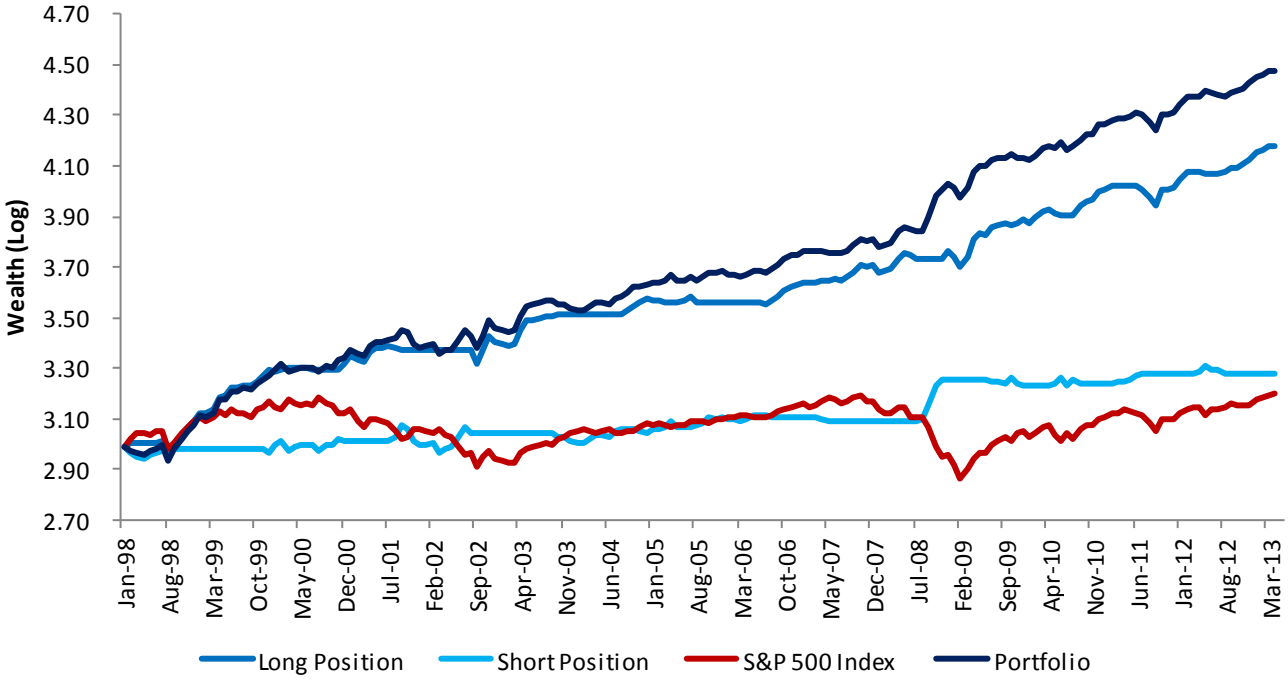
*Source: Deutsche Bank Quantitative Strategy*

Figure 59: Market Timing Quantitative Portfolio – no leverage portfolio returns (i.e. net long + short weight = 100%)




*Source: Deutsche Bank Quantitative Strategy*

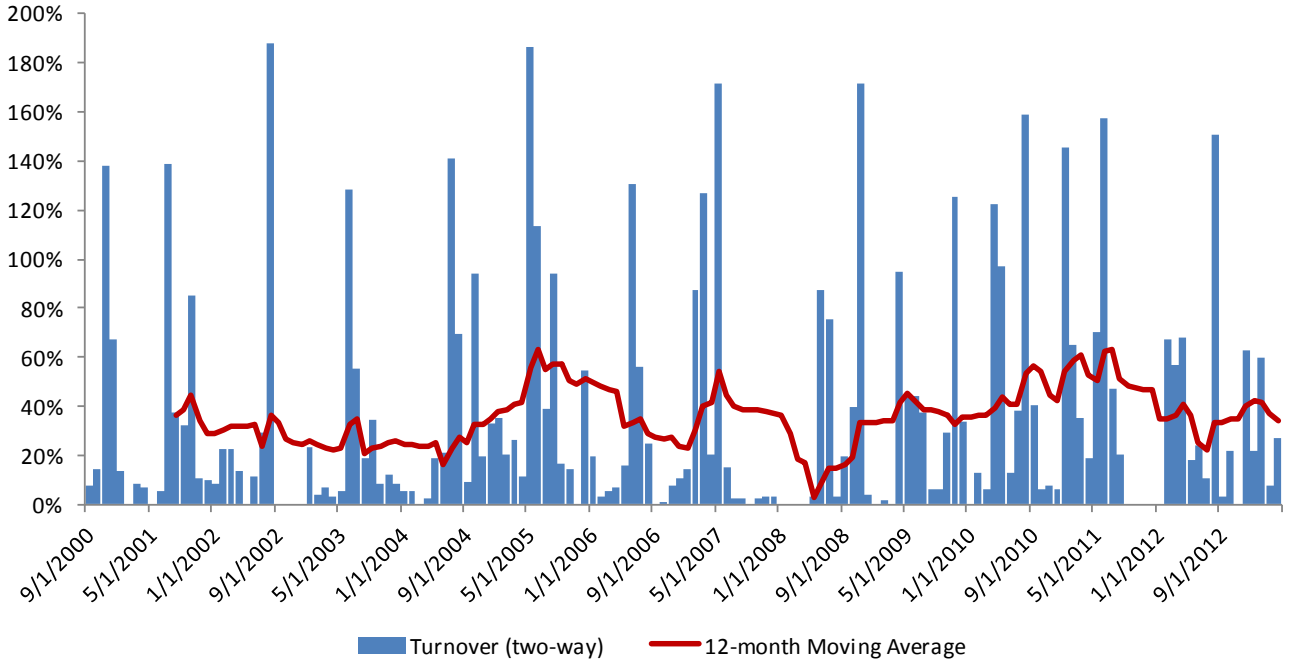
Figure 60: Market Timing Quantitative Portfolio – Wealth Curve




The performance of the portfolio was stable during the backtesting period, especially considering that the market dropped over 50% from the peak in late 2007 to the bottom in Febraury 2009. The majority of the portfolio returns came from the long positions, which is consistent with the test results in the Iron Age.

The beauty of combining market timing and quantitative approaches is that good performance does not necessary mean high turnover. The lengthy holding period for the signals suggests the long/short portfolio should be stable once constructed. As shown in Figure 61, there are several high turnover months during the backtest period, however the median two-way monthly turnover is 16% per month.

Figure 61: Portfolio turnover (two-way)




*Source: Deutsche Bank Quantitative Strategy*

## Quantitative Market Strength Index (QMSI)

We know in the Iron Age that the S&P 500 Index tends to increase 10.4% annually on average during the periods with Buy signals, and since the long positions are the major contributors in the monthly long/short portfolio, we expect the total weight of the long positions should also have market timing ability.

We examine our backtesting results and reveal the relationship between the weight in long positions and 1-month forward index returns, as shown in Figure 62.

Figure 62: The correlation between long position weights and returns

| Long Weight | # of Month | Long Position Return | Short Position Return | S&P 500 Index 1-month Forward Return |
|---|---|---|---|---|
| >50% | 105 | 2.76% | -0.03% | 0.90% |
| <50% | 77 | 0.02% | 1.14% | -0.41% |
| >80% | 87 | 3.13% | -0.07% | 0.86% |
| <20% | 55 | -0.03% | 1.30% | -0.76% |

*Source: Deutsche Bank Quantitative Strategy*

Results in Figure 63 suggest the correlation between the sum of weights in the long positions and the future market returns is strong enough to serve as a market timing indicator. We propose a Quantitative Market Strength Index (QMSI) as follows:

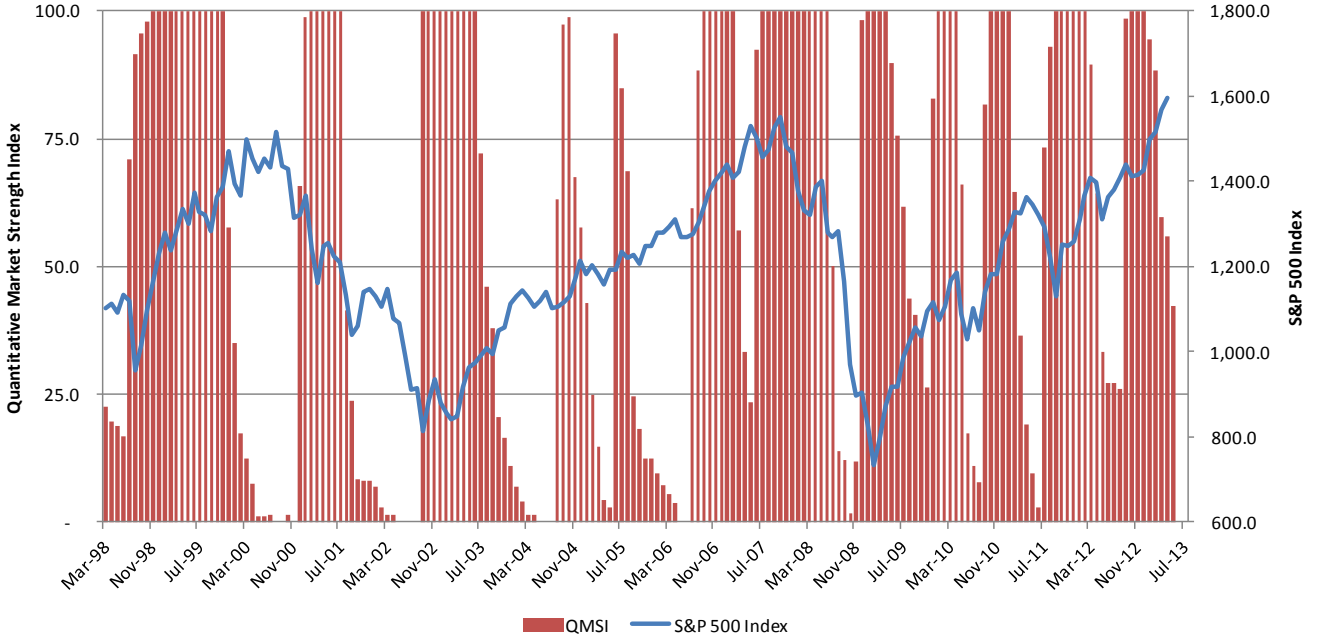
$$QMSI_t = \sum_{i=1}^{N} W_{i,t} I(i,t)$$

where $N$ is the number of stock in the portfolio $W_{i,t}$ is the weight of stock $i$ at time $t$, and $I(i,t)$ is defined as:

$$I(i,t) = \begin{cases} 1, W_{i,t} > 0 \\ 0, W_{i,t} < 0 \end{cases}$$

The value of QMSI is from 0 to 100. When QMSI is greater than 50, the market is generally in an uptrend; when the indicator drops below 50, the index is likely to fall. Figure 63 shows the historical QMSI and the S&P 500 Index.

Figure 63: Quantitative Market Strength Index




*Source: Deutsche Bank Quantitative Strategy*

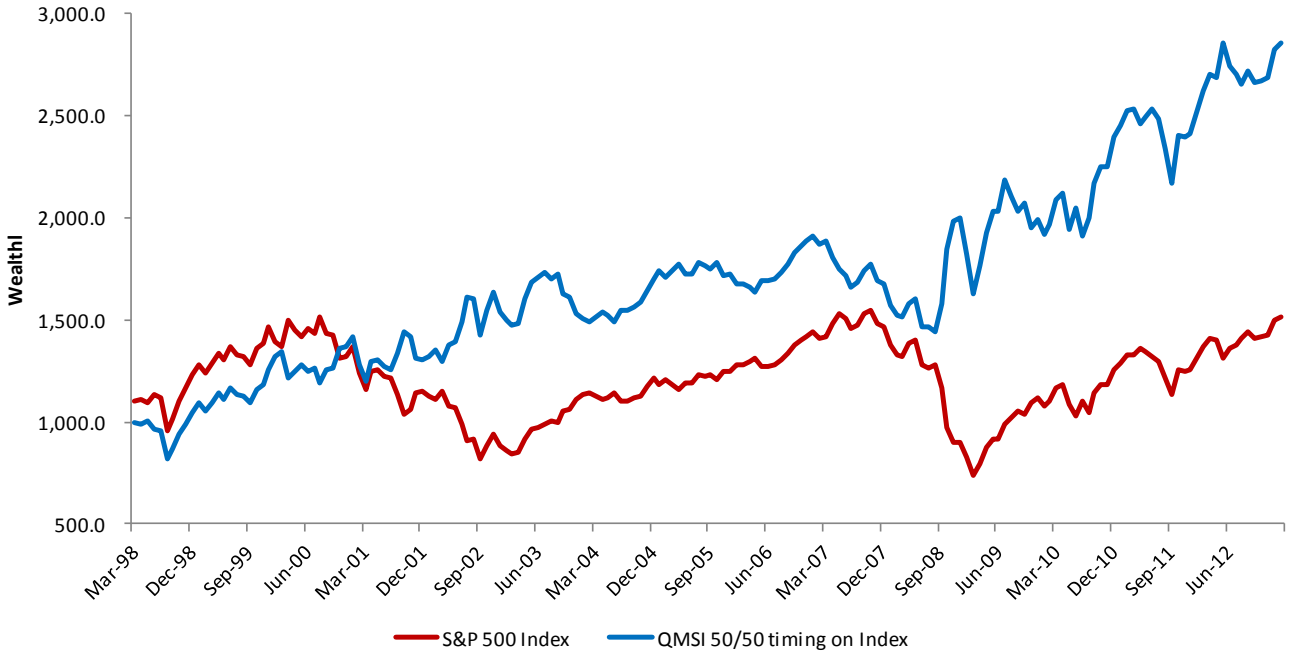
Assuming we want to get exposure to the whole equity market instead of trading a stock portfolio, the QMSI can help us make better decisions. We build a market index trading strategy based on the information in Figure 62 and Figure 63.

QMSI 50/50 timing strategy:

- If QMSI>50, long S&P 500 Index
- If QMSI<50, short S&P 500 Index

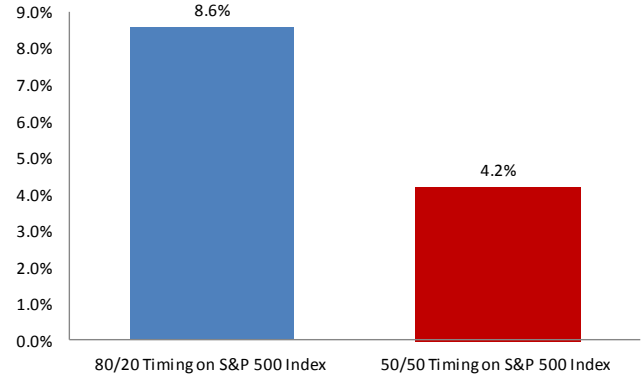
As we can see in Figure 64 and Figure 66, this strategy outperforms the buy and hold strategy in terms of both returns and risk adjusted returns since March 1998.

## Figure 64: Timing S&P 500 Index with QMSI



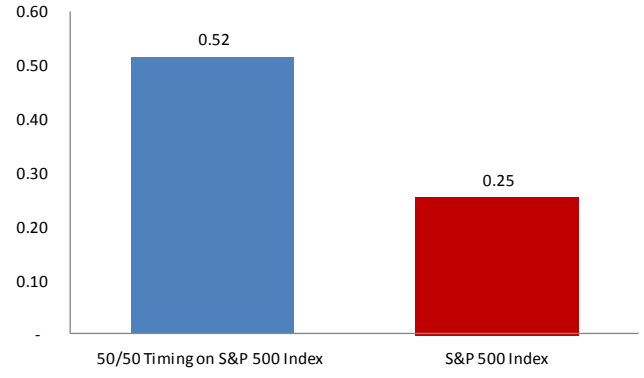

*Source: Deutsche Bank Quantitative Strategy*

## Figure 65: Timing with QMSI - Annualized Returns




*Source: Deutsche Bank Quantitative Strategy*

## Figure 66: Timing with QMSI – Sharpe Ratio

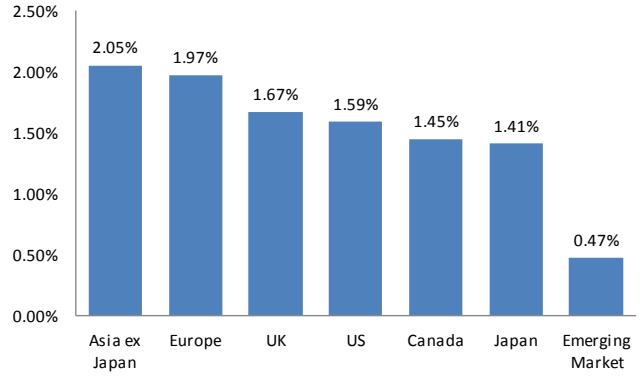



*Source: Deutsche Bank Quantitative Strategy*

## The great globalization

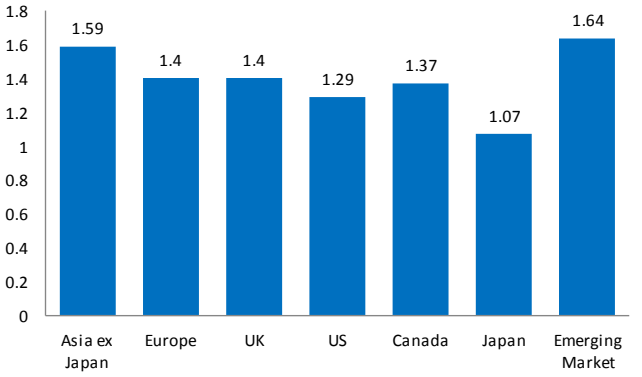
We construct monthly portfolios with the methodology described earlier in this section in global markets. County-based tests are in local currencies, while in regional tests, both prices and returns are converted to US dollars. Since short selling is more difficult to implement in global markets than in US market and technical indicators have shown across the board stronger predictive power on the long side, we focus on long-only strategy. QMSI is used to allocate the weight to the long-only portfolio, as illustrated in Figure 57.

Figure 67: Global results – monthly return




*Source: Deutsche Bank Quantitative Strategy*

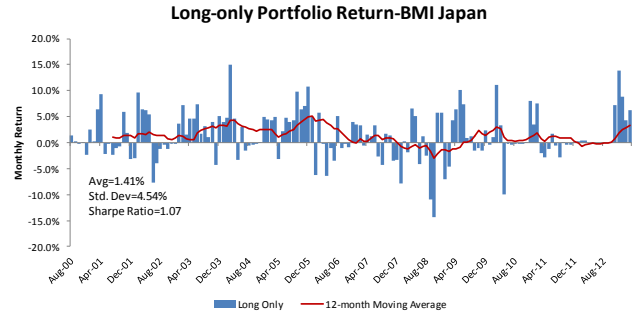
Figure 68: Global results – Sharpe ratio




*Source: Deutsche Bank Quantitative Strategy*

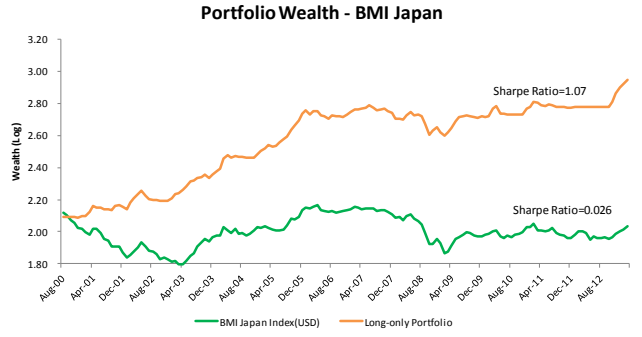
Overall, the strategy of combining technical and quantitative approaches has consistent performance across different countries and global regions in terms of risk adjusted returns.

Figure 69: BMI Japan – Portfolio Returns



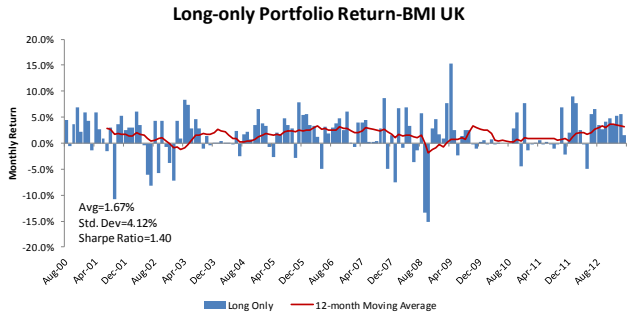

*Source: Deutsche Bank Quantitative Strategy*

Figure 70: BMI Japan – Portfolio & Benchmark



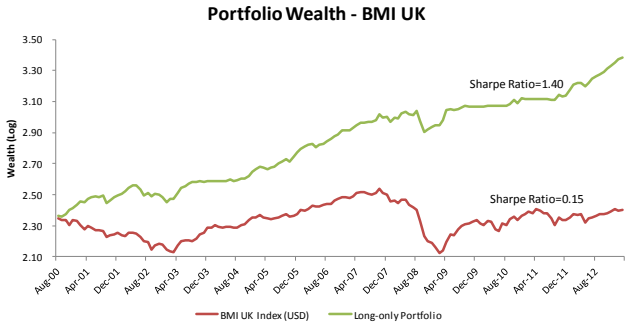

*Source: Deutsche Bank Quantitative Strategy*

## Figure 71: BMI UK – Portfolio Returns



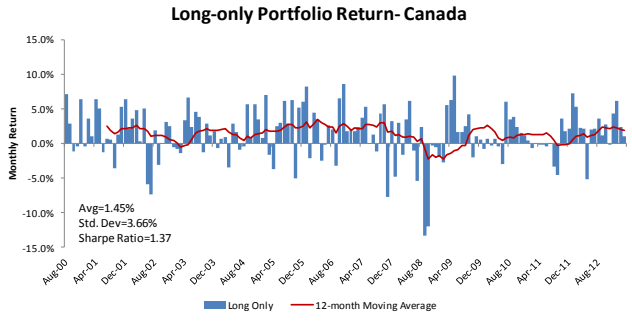

*Source: Deutsche Bank Quantitative Strategy*

## Figure 72: BMI UK – Portfolio & Benchmark



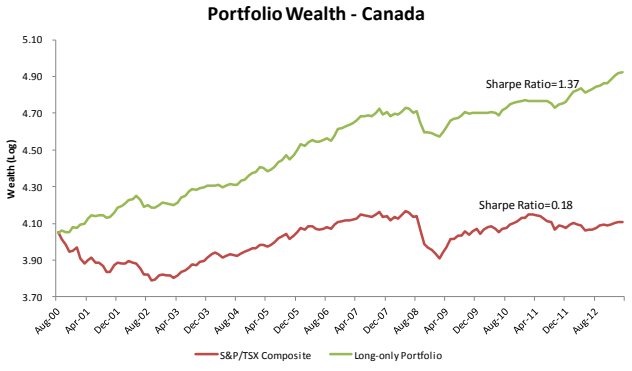

*Source: Deutsche Bank Quantitative Strategy*

## Figure 73: Canada – Portfolio Returns



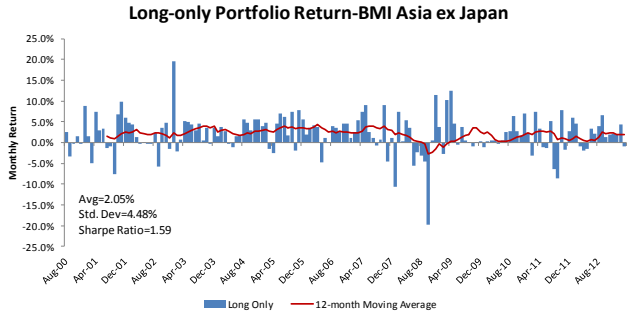

*Source: Deutsche Bank Quantitative Strategy*

## Figure 74: Canada – Portfolio & Benchmark



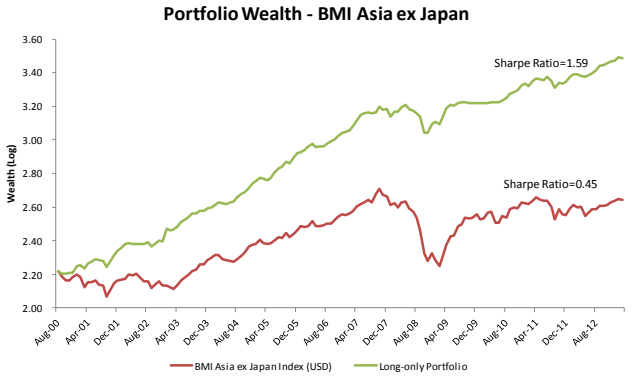

*Source: Deutsche Bank Quantitative Strategy*

## Figure 75: BMI Asia ex Japan – Portfolio Returns



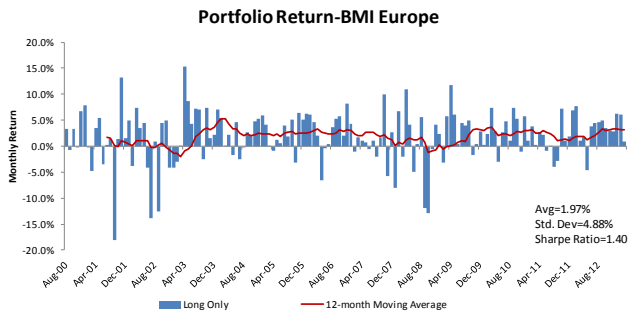

*Source: Deutsche Bank Quantitative Strategy*

## Figure 76: BMI Asia ex Japan – Portfolio & Benchmark



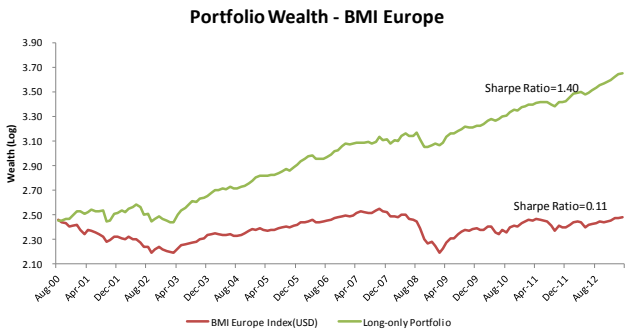

*Source: Deutsche Bank Quantitative Strategy*

## Figure 77: BMI Europe – Portfolio Returns



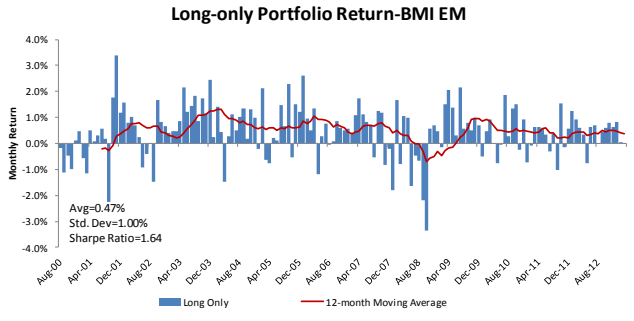

*Source: Deutsche Bank Quantitative Strategy*

## Figure 78: BMI Europe – Portfolio & Benchmark



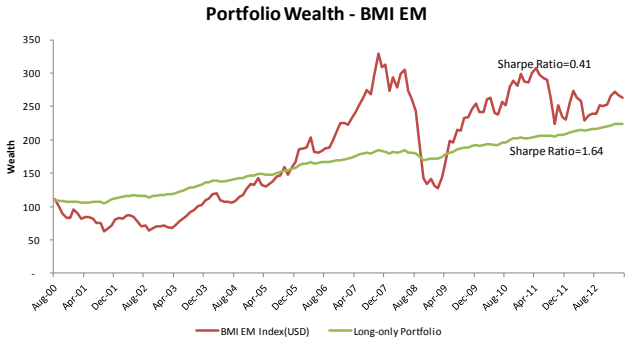

*Source: Deutsche Bank Quantitative Strategy*

## Figure 79: BMI EM – Portfolio Returns



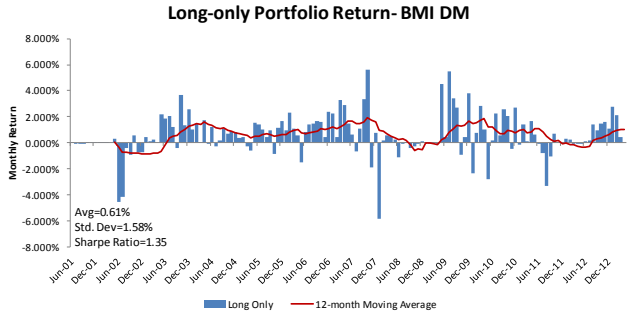

*Source: Deutsche Bank Quantitative Strategy*

## Figure 80: BMI EM – Portfolio & Benchmark



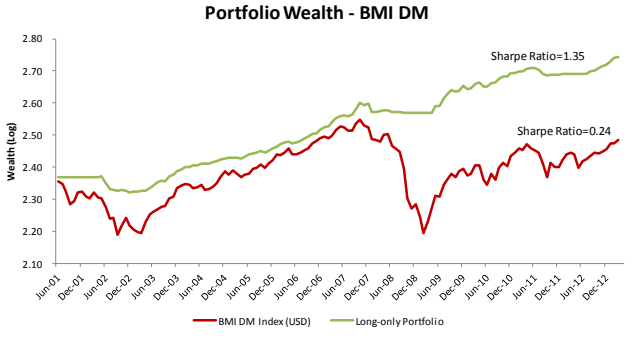

*Source: Deutsche Bank Quantitative Strategy*

## Figure 81: BMI DM – Portfolio Returns




*Source: Deutsche Bank Quantitative Strategy*

## Figure 82: BMI DM – Portfolio & Benchmark




*Source: Deutsche Bank Quantitative Strategy*

## A country rotation strategy

We extend the utilization of the methodology described earlier in this section to the country index level. The universe is 45 MSCI All Country World total return USD indexes, as shown in Figure 83.

Figure 83:Index universe

| Bloomberg Ticker | Index Name | Bloomberg Ticker | Index Name |
|---|---|---|---|
| GDDUCA Index | MSCI Canada Total Return, USD | GDDUSG Index | MSCI Singapore Total Return, USD |
| GDDUUS Index | MSCI USA Total Return, USD | GDUEBRAF Index | MSCI Brazil Total Return, USD |
| GDDUAT Index | MSCI Austria Total Return, USD | GDUESCH Index | MSCI Chile Total Return, USD |
| GDDUBE Index | MSCI Belgium Total Return, USD | GDUESCO Index | MSCI Colombia Total Return, USD |
| GDDUDE Index | MSCI Denmark Total Return, USD | GDUETMXF Index | MSCI Mexico Total Return, USD |
| GDDUFI Index | MSCI Finland Total Return, USD | GDUESPR Index | MSCI Peru Total Return, USD |
| GDDUFR Index | MSCI France Total Return, USD | GDUESCZ Index | MSCI Czech Republic Total Return, USD |
| GDDUGR Index | MSCI Germany Total Return, USD | GDUESEG Index | MSCI Egypt Total Return, USD |
| GDUESGE Index | MSCI Greece Total Return, USD | GDUESHG Index | MSCI Hungary Total Return, USD |
| GDDUIE Index | MSCI Ireland Total Return, USD | GDUESMO Index | MSCI Morocco Total Return, USD |
| GDUESIS Index | MSCI Israel Total Return, USD | GDUESPO Index | MSCI Poland Total Return, USD |
| GDDUIT Index | MSCI Italy Total Return, USD | GDUESRUS Index | MSCI Russia Total Return, USD |
| GDDUNE Index | MSCI Netherlands Total Return, USD | GDUESSA Index | MSCI South Africa Total Return, USD |
| GDDUNO Index | MSCI Norway Total Return, USD | GDUESTK Index | MSCI Turkey Total Return, USD |
| GDDUPT Index | MSCI Portugal Total Return, USD | GDUETCF Index | MSCI China Total Return, USD |
| GDDUSP Index | MSCI Spain Total Return, USD | GDUESIA Index | MSCI India Total Return, USD |
| GDDUSW Index | MSCI Sweden Total Return, USD | GDUESINF Index | MSCI Indonesia Total Return, USD |
| GDDUSZ Index | MSCI Switzerland Total Return, USD | GDUESKO Index | MSCI Korea Total Return, USD |
| GDDUUK Index | MSCI UK Total Return, USD | GDDUMAF Index | MSCI Malaysia Total Return, USD |
| GDDUAS Index | MSCI Australia Total Return, USD | GDUESPHF Index | MSCI Philippines Total Return, USD |
| GDDUHK Index | MSCI Hong Kong Total Return, USD | GDUESTW Index | MSCI Taiwan Total Return, USD |
| GDDUJN Index | MSCI Japan Total Return, USD | GDUESTHF Index | MSCI Thailand Total Return, USD |
| GDDUNZ Index | MSCI New Zealand Total Return, USD | | |

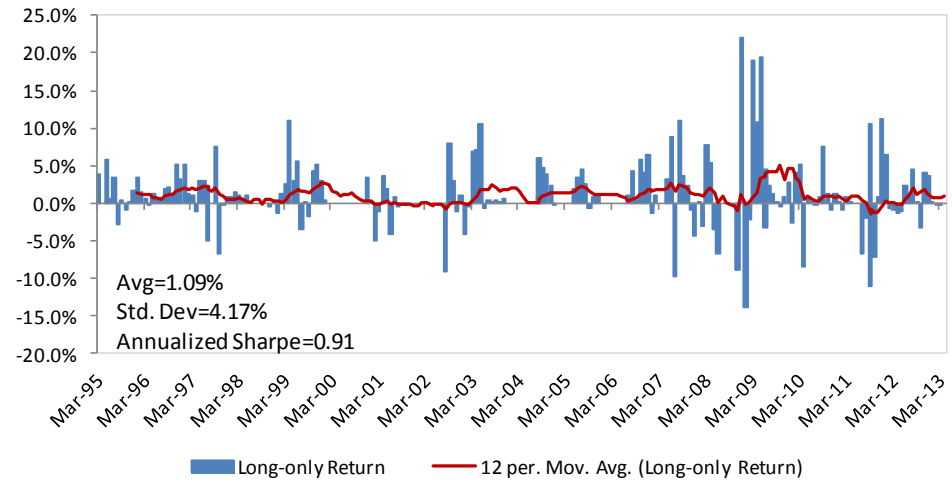
*Source: Deutsche Bank Quantitative Strategy*

First, we run the Iron Age signal system on 45 MSCI country indexes. The market signal is derived from the large cap index Dow Jones Industrial Average Index and the small cap index Russell 2000 Index (i.e. we use the relative performance of US large and small caps for all markets).

Next we define the trading momentum factor (WIN) based on the trading history of each index. At each month end, we rank the WIN factor from high to low, and pick the top 10 country indexes as potential investment candidates. If any of these candidates is in buy signal, i.e. market signal + stock signal > 0, we will allocate 10% weight to the equity market of that country. The portfolio is held for one month and then we repeat the same rebalance process.

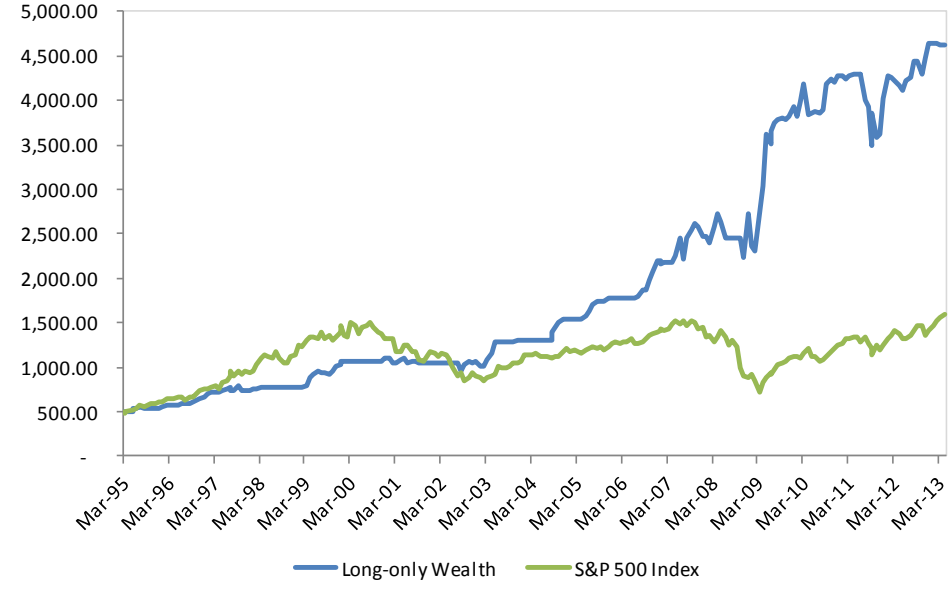
We also calculate the Quantitative Market Strength Index (QMSI) across the 45 countries to determine what our model says about equities in general. The current reading of QMSI is zero, which indicates that we are bearish on equities in general.

Figure 84: Long-only country rotation returns



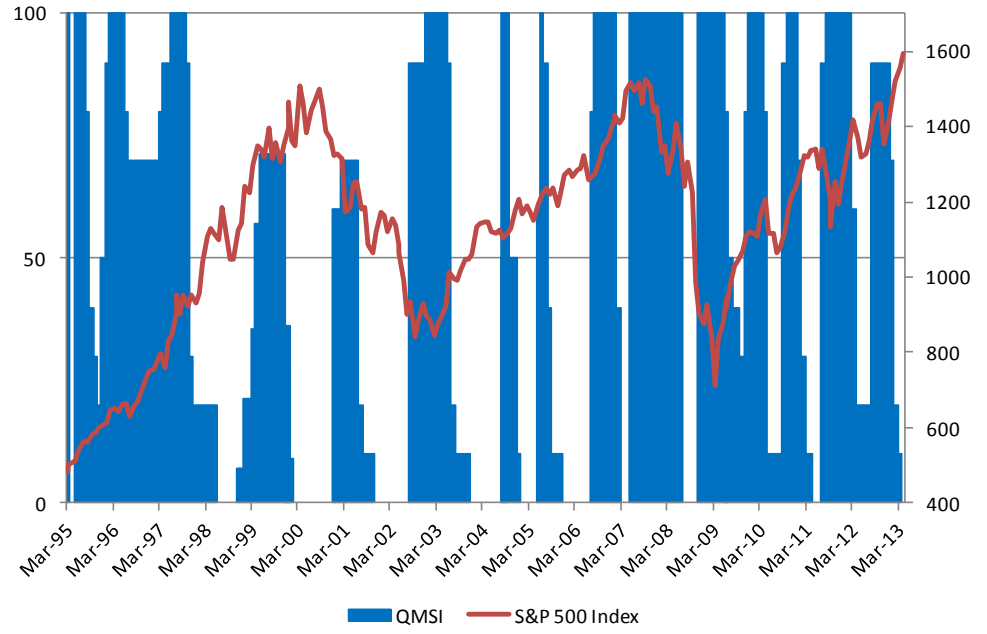

*Source: Deutsche Bank Quantitative Strategy*

Figure 85: Long-only country rotation vs benchmark




*Source: Deutsche Bank Quantitative Strategy*

Figure 86: Country-based Quantitative Market Strength Index (QMSI)




*Source: Deutsche Bank Quantitative Strategy*

# References

Cahan, R., J. Cahan, and B. Marshall, 2008,"Does intraday technical analysis in the US equity market have value?", *Journal of Empirical Finance*, Volume 15, Issue 2.

Chen et al., 2012, "Rebooting Revisions", *Deutsche Bank Quantitative Strategy*, 11 September 2012

Edwards, R. and J. Magee, "Technical Analysis of Stock Trends", 9th edition, BN Publishing

Han, Y., K. Yang, and G. Zhou, 2011, "A new anomaly: The cross-sectional profitability of technical analysis", SSRN working paper, available at http://ssrn.com/abstract=1656460

Jussa et al., 2011, "Technically Savvy Alpha", *Deutsche Bank Quantitative Strategy*, 6 May 2011

Jussa et al., 2013, "The Socially Responsible Quant", *Deutsche Bank Quantitative Strategy*, 24 April 2013

Le Binh et al., 2011, "Quantiles: Technicalities in Asia", Deutsche *Bank Quantitative Strategy*, 17 November 2011

Luo et al., 2011, "Signal Processing: Quant Tactical Asset Allocation", *Deutsche Bank Quantitative Strategy*, 19 September 2011

Malkie, B. G., 2011, "A Random Walk Down Wall Street"

Robert D Edwards and John Magee, Technical Analysis of Stock Trends, 9th edition

Wang et al, 2012, "Signal Processing: The rise of the machines", *Deutsche Bank Quantitative Strategy*, 5 June 2012

Wang et al, 2013, "Signal Processing: The rise of the machines II", *Deutsche Bank Quantitative Strategy*, 23 January 2013

Zhou, X. and M. Dong, 2004, "Can Fuzzy Logic Make Technical Analysis 20/20?", *Financial Analysts Journal*, Volume 60, Number 4

# Appendix 1

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