

A Refined MACD Indicator – Evidence against the Random Walk Hypothesis?

By

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Abstract

Rigorous testing of the widely used MACD indicator results in a surprisingly low success rate of 32.73% for the individually tested NASDAQ-100 stocks over a 10-year period. This study derives two methods, which address the shortcomings of the MACD indicator. The methods are tested out-of-sample to address data-snooping concerns, i.e. to reduce the chance of

falsely rejecting the null-hypothesis of no predictability. One version of the second derived method, named MACDR2, results in a success-rate of 89.39%. The performance of method MACDR2 is positively correlated to the volatility of the stock and can be enhanced with option trading. However, the risk-adjusted Sharpe ratio, which is highly sensitive to the

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implied volatility used in the Black-Merton model, shows mixed results. Shorter or longer exponential moving averages do not improve the success rate of the traditional MACD indicator. Yet the success rate of method MACDR2 is slightly positively correlated to longer exponential moving averages.

Most versions of the method MACR2 outperform the benchmark of holding a riskless security, the Treasury bond and holding the underlying asset, the NASDAQ-100. Thus, this study provides evidence against the Random Walk Hypothesis. However, the results are weakened significantly, if transaction costs and maximum trading constraints are incorporated in the study.

Key words: Technical Analysis, Moving Average, MACD Indicator, Random Walk

JEL classification: C12, G15

1. Introduction

Technical Analysis is a methodology that tries to forecast the prices of financial securities by observing the pattern that the security has followed in the past. There are numerous methods within Technical Analysis, which are principally independent from each other.

Over the last two decades, Technical Analysis has become a popular way to predict stock prices in trading practice. Many investors and traders are using methods of Technical Analysis to support their trading decisions.

Technical Analysis has its main justification in the field of psychology, i.e. self-fulfilling prophecy: Due to the fact that many traders trade according to the rules of Technical Analysis, and computers programs give buy and sell signals based on that theory, the market is assumed to move according to the principles of Technical Analysis.

Due to its heuristic nature, Technical Analysis can hardly be proven mathematically. Consequently the proof has to be done empirically. It is quite surprising though that hardly any rigorous empirical testing of the methods of Technical Analysis has been done. Among the few who tested the MACD indicator are Brock, Lakonishok and LeBaron (1992), who tested several moving averages and found them useful in predicting stock prices. However, their benchmark was merely holding cash. Seyoka (1991) tested the MACD indicator from 1989 to 1991 on the S&P 500. His results questioned the indicators' usefulness. Sullivan, Timmermann and White (1999) found superior performance of moving averages for the Dow Jones Industrial Average for in-sample data. However, their results showed no evidence of outperformance for out-of-

sample data.

The objective of the study is to investigate, whether a refined method of the MACD indicator can outperform a benchmark of holding a riskless security as a Treasury bond or holding the underlying asset, i.e., individual stocks of the NASDAQ-100. Thus, this study is challenging the random walk hypothesis.

The traditional MACD Indicator

One of the most popular methods of Technical Analysis is the MACD, Moving Average Convergence Divergence, indicator. The MACD uses three exponentially smoothed averages to identify a trend reversal or a continuation of a trend.

The indicator, which was developed by Gerald Appel in 1979,

reduces to two averages. The first, called the MACD1 indicator, is the difference between two exponential averages, usually a 26-day and a 12-day average. The second, called Signal indicator, is the 9-day moving average of the MACD1 indicator.

The terms “convergence” and “divergence” refer to a narrowing and widening of the difference of the MACD1 and the Signal indicator: A buy signal is given, when the more volatile average, the MACD1 indicator, crosses the less volatile average, the Signal indicator, from beneath. If the MACD1 line crosses the Signal line from above, a sell signal is given. The bigger the angle of the crossing, the more significant the buy or sell signal is. Let's look at an example. From December 28th 1998 to December 28th 1999, the price of Microsoft moved as in figure 1:

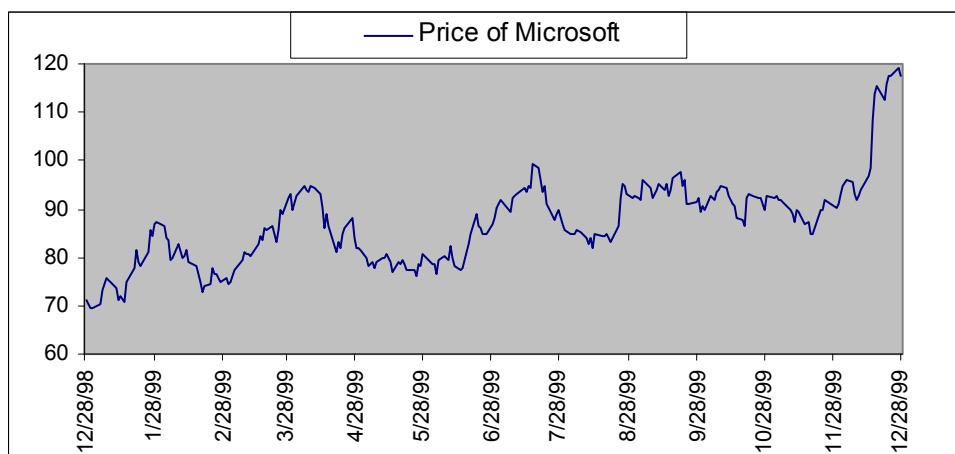


Figure 1: The price movement of Microsoft

From the stock price movement in Figure 1 we get the following moving average

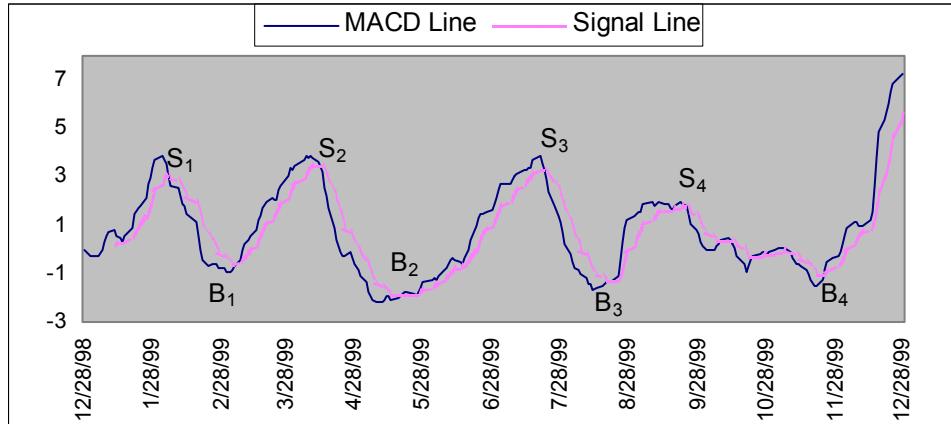


Figure 2: MACD1 and Signal indicator resulting from Figure 1

From Figure 1 and 2, we can derive that the buy signals B_1 , B_2 , B_3 and B_4 all worked well: The price in Figure 1 increases after the signals. All sell signals S_1 , S_2 , S_3 and S_4 also worked well. The price in Figure 1 decreases after each sell signal.

From Figure 1 and 2, we can also recognize the lagging feature of the MACD indicator. All buy and sell signals occurs shortly **after** the bottom or top of the price movement.

The reason why the traditional MACD indicator works so well in Figures 1 and 2 is the fact that Microsoft moved in ideal trends, especially from December 28, 1998 to August 28, 1999. During this period, we can recognize clear upward and downward trends with a period of 30 to 50 days. In this environment the traditional MACD indicator works well.

From August 28, 1999 to November 18, 1999, we had a sideways market. Therefore, no clear buy or sell signal, meaning no high degree crossing of the MACD and Signal indicator, was given during that period.

However, stock prices do not always exhibit the MACD favorable trends as in Figure 1. Often a trend, although believed strong, falters. Also, since the MACD is a lagging indicator, often the reversal of the trade is done too late. These two drawbacks are addressed in this article and methodologies are derived to overcome the shortcomings.

The exponential moving average (EMA) used in the MACD method is calculated as

$$(1) \text{ EMA}_t = (P_t K - \text{EMA}_{t-1} K) + \text{EMA}_{t-1}$$

where

EMA_t : current value of exponential moving average

P_t = current price of underlying asset

$K = 2 / (\text{number of periods} + 1)$

Equation (1) implicitly includes the exponential smoothing: If $K = 0.2$, (number of periods is 9) and $EMA_{t-1} = 10$, it follows that a current price of $P_t = 12$ leads to an $EMA_t = 10.4$, a price $P_t = 8$ leads to $EMA_t = 9.6$; a price $P_t = 4$ leads to an $EMA_t = 8.8$.

2. Analysis

This study tests the traditional MACD indicator and derived two methods, MACDR1 and MACDR2 (R: Refinement), which significantly improve the MACD trading results and outperform the benchmark of holding a no-risk security, the Treasury bond and holding the underlying instrument, the NASDAQ-100.

A big problem when testing technical analysis rules is the aspect of data snooping, which increases the chance of falsely rejecting the null hypothesis, which in this study is the random walk hypothesis of no predictability. To address data-snooping concerns, the methods MACDR1 and MACDR2 are derived from data of the Dow Jones Industrial Average from May 30, 1989 to May 30, 1999. The methods were derived firstly by simple visual observation of the

functioning of the MACD indicator and then by numerical trial and error calculations. The methods were then tested out-of-sample for the NASDAQ-100 stocks, individually, for the same 10-year time period.

Altogether, this study uses 314,645 daily closing prices and 92,328 resulting buy and sell signals to verify the methods involved.

Model MACDR1

A crucial issue when using moving averages is to determine the correct timing of the opening purchase or sell. The first model, called MACDR1, attempts to eliminate buy and sell signals when the averages MACD1 and the Signal are crossing each other frequently in a short period of time, thus in a case, where there is no clear trend. Instead, the trading signal is given three days after the actual crossing if the trend is still intact. Thus, the position is opened at the closing price of the third day after the crossing, if no crossing has appeared on day 2 and 3.

A further important issue is to close the trade at the right point in time. Since the MACD indicator is a lagging indicator, the reversal of a successful trade is often done too late, especially because a trend reversal often happens very quickly. This fast reversal is hard to anticipate, but it is devastating when failed to predict, because the first few

days after the reversal often have the most significant price move.

Model MACDR1 (and model MACDR2) resolve this problem by indicating a closing signal when a predetermined profit has been reached. In this study we test profit levels of 3% and 5%. Thus, the models gives a signal to close an open position when a 3% or 5% target gain has been reached or if another crossing occurs before the target is reached.

A lower target will naturally be reached more often but there is an opportunity cost involved when closing a position too early and missing out on bigger profits.

Model MACDR2

Model MACDR2 is a further refinement of method MACDR1. Method MACDR2 produces trading signals when the trend is stronger than method MACDR1. It naturally generates fewer buy and sell signals than model MACDR1, but it has a higher success rate for each trade.

The basic concept of model MACDR2 is the same as in model MACDR1. However, the buy or sell signal is given, if the difference between the moving averages is bigger or equal than a certain percentage of the stock price at the end of the third day after a crossing. We test crossing-levels from 0.5% to 3.5%. For levels

over 3.5%, hardly any trading signals occur.

To illustrate method MACDR2, let's assume the stock price is \$100, the MACD1 = 2 and the Signal = 1 on the third day after a crossing. The difference between the averages is 1, which is 1% of the stock price. This would generate a trading signal for crossing-levels bigger or equal than 1%. This method assures that the stock movement at the beginning of a trend is significant and not a random movement in a narrow trading range.

In this study, the correlation between model MACDR2 and the volatility of each stock as well as the market capitalization of each stock are tested.

Furthermore, it is shown that the trading results can be improved significantly, when combined with option trading.

We also test if the results of the traditional MACD indicator and our method MACDR2 can be improved when moving averages of different time lengths are used.

Finally, we compare the outcome of the method MACDR2 with two benchmarks, the risk-less Treasury bond and the underlying instrument, the NASDAQ-100 to challenge the random walk hypothesis.

3. Results

The traditional MACD

The results from the empirical testing of the traditional MACD indicator were surprisingly poor. For the individually, out-of-sample tested NASDAQ-100 stocks over a 10-year period, only 32.73% of the total trades generated a profit. A similar result is obtained for in sample tested 30 stocks of the Dow Jones Industrial Average over the last 10 years. Here only 32.14% of all trades resulted in a profit. Thus, the traditional MACD indicator can almost be regarded as a contra-indicator.

The reasons for the poor results are twofold: 1) A weak buy or sell signal is given and no significant trend follows. 2) Due to the lagging nature of the MACD indicator, the reversal of the trade is done too late.

The model MACDR1

As mentioned in section 2., model MACDR1 addresses these two weaknesses. The results of model MACDR1 are shown in table 1:

Two scenarios are tested regarding model MACDR1. The position is closed when a gain of greater equal 3% is achieved and when a gain of greater equal 5% is achieved. For the 3% target, the actually achieved average profit is 4.92%. For the 5% target, the actually achieved average profit is 6.88 %.

As seen in Table 1, model MACDR1 outperforms the traditional MACD model, which resulted in a 32.73% success rate. The success rate of model MACDR1 is on average 61.62% for the 3% target. The bullish success rates are as expected a little bit higher than the bearish ones, considering that this study is done during a bull market. It is also encouraging to see that the bearish signals are successful more than 57% in the bull market. This study shows that model MACDR1 is able to find profitable short-selling opportunities even in a strong bull market.

Model MACDR1 generated significantly better trading results than the traditional MACD model. But when analyzing the simulated trades it became clear that model MACDR1 sometimes generated trade signals even

	<u>3% target</u>	<u>5% Target</u>
Average success rate of all signals	61.62%	52.17%
Average profit per trade	4.92%	6.88%
Average success rate of bullish signals	65.88%	56.61%
Average success rate of bearish signals	57.36%	47.72%

Table 1: Results from model MACDR1 for the NASDAQ-100 stocks

if the trend was weak. Model MACDR2 is an improvement of model MACDR1 in terms of trend-identification.

The Model MACDR2

The results of model MACDR2, which gives a buy or sell signal if the difference between the MACD1 and Signal indicator is bigger than a certain percentage of the stock price, are seen in Table 2.

Model MACDR2 improves the results of model MACDR1 significantly. As to be expected, the higher the degree of crossing of the MACD1 and Signal line, the higher the success rate was. This comes at the expense of fewer trading signals.

Model MACDR2 and Option Trading

The characteristics of model MACDR2 make it highly suitable for option trading because the holding period is on average only 5.06 days,

thus, the time decay of the long option position is small. In model MACDR2, for the 1.5 % crossing-level, 70.76% of all trades generated an average profit of 5.94%. This profit can be increased significantly with the use of options and their leverage effect: $\Delta C/C / \Delta S/S$ (C : Call price, S : Spot Stock price). The leverage is the higher the shorter the option maturity and the lower the volatility.

In this analysis, we use the same buy and sell criteria as in method MACDR2 for a 1.5% crossing-level. When a buy signal occurs, a call is bought, when a sell signal occurred, a put is bought. The calls and puts are at-the-money spot (the strike price = stock spot price), and priced using the historical volatility of each stock, together with a 4.5% interest rate and a 30-day option maturity¹. The time decay for each holding period is subtracted from the profit or loss of the trade.

¹ All calculations are done on TRADE SMART, www.dersoft.com

To price the calls and puts we used the standard Black-Merton approach

$$C = S e^{-qT} N(d_1) - K e^{-rT} N(d_2) \text{ and}$$

$$P = K e^{-rT} N(-d_2) - S e^{-qT} N(-d_1)$$

where

$$d_1 = \frac{\ln(\frac{S}{K}) + \frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}} \quad \text{and}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

C : Call price, European style

P : Put price, European style

S : Price of underlying stock

K : Strike price

T: Option maturity in years

N(d): Cumulative standard normal distribution at d

r: Risk-free annual interest rate, continuously compounded

q: Annual dividend yield, continuously compounded

σ : Annual volatility of the stock

At the time of the study (Fall 2000), eleven of the NASDAQ-100 stocks paid a dividend, so the Black-Merton approach, which includes dividends, is warranted. The average dividend yield of these 11 stocks was 0.62 pa.

Since an at-the-money call and put with a 60% volatility and a 30-day option period has a leverage of 6.95 and 6.17 respectively, we expected the trading profit to increase by a factor of

6.17 to 6.95 minus the time decay of the option. In our study of the NASDAQ-100 stocks over the last 10 years, the average trading profit increases from 5.94% to 13.06% occurred. Thus, when option trading is used on the basis of method MACDR2 with the 1.5% crossing-level, we derived the result that 70.76% of all trades generate an average per trade profit of 13.06%.

Naturally, the use of leverage will increase any ex post positive mean strategy. Crucial is whether the risk-adjusted return increases with the help of options. To answer this question we calculated the Sharpe ratio for the holding stocks of the NASDAQ-100 and holding a call or put on the stocks of the NASDAQ-100:

$$S(N) = (r_N - R_f) / \text{Stdev}(N)$$

$$S(O_N) = (r_{O_N} - R_f) / \text{Stdev}(O_N)$$

where

S : Sharpe ratio

N: Stock of the NASDAQ-100

O_N : Option (call or put) on N

r_N : Average of return of N

r_{O_N} : Average return of trading the option

R_f : Average annual risk free rate of return

Stdev: Standard Deviation of the annual percentage returns of N

Stdev: Standard Deviation of the annual percentage returns of O_N

The yearly Sharpe ratio for the NASDAQ-100 stocks, S (N), using a risk free Treasury yield of 8.268%

resulted in 12.36%. The yearly Sharpe ratio when trading options, $S(O_N)$, resulted in 55.65%. The later result was achieved by pricing the call and put with their individual historical 10-year volatility. This is slightly misleading, since the implied volatility has steadily increased in the past. Figure 3 shows the development of the implied

volatility for the VIX and VXN. The VIX is an index, traded on the CBOE, which reflects the implied volatility of 8 at-the-money, 30-day options on stock of the S&P 500. The VXN reflects the implied volatility of an at-the-money, 30-day option on the NASDAQ-100. This contract was introduced on the CBOE on January 22, 2001.

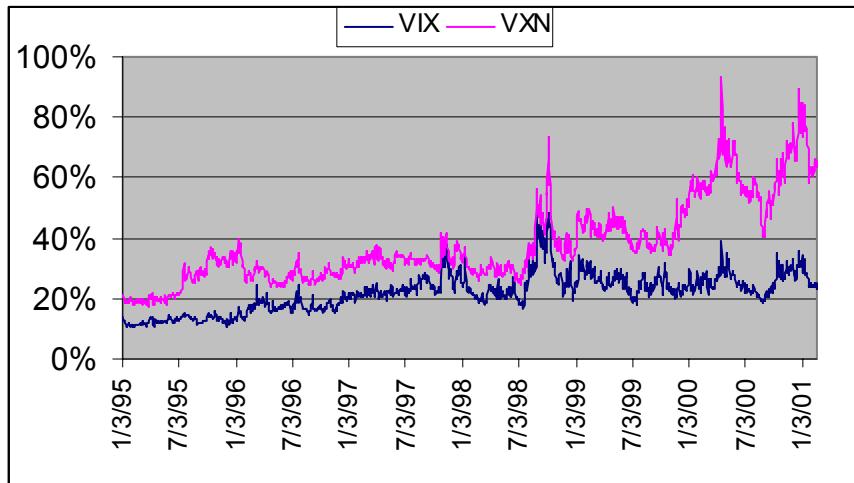


Figure 3: The implied volatility indices VIX and VXN from January 1st, 1995 to February 15, 2001

As to be expected, the Sharpe ratio for options is highly sensitive to the implied volatility used in the Black-Merton model. When using the average implied volatility of the VXN from January 1st to February 15, 2001, 68.16%, the Sharpe ratio $S(O_N)$ decreases from 55.65% to 39.50%. The Sharpe ratio of trading the individual stocks and trading option on these stocks is identical at 12.36% for an implied volatility of 85.35%, a level

that was even exceeded in April and December 2000. In this case, the Sharpe ratio of trading stocks exceeded the Sharpe ratio of trading options. The Sharpe ratio $S(O_N)$ is also highly sensitive with respect to the option maturity T . Increasing the option maturity from 30 to 45 days, decreases $S(O_N)$ to 36.78%; a decrease of the option maturity to 15 days increases $S(O_N)$ to 82.74%, when an implied volatility is used in the Black-Merton

model, which is identical to the historical volatility.

Model MACDR2 and Volatility

An interesting question is whether the success rate of model MACDR2 is correlated to the volatility of a stock. We calculated the 30-day volatility for each stock and annualized with a factor of 260 trading days. The average annual volatility was then used for the graph below. Figure 4 shows the success rate of Model MACDR2 for a 0.5% crossing level and the volatility of the stock.

Figure 4 shows a positive correlation with a p-level of 8.18E-09, t-statistics of 6.32 and an F-value of 40.02. However, the correlation coefficient R is unsatisfactory low with 0.54. The overall slightly positive

correlation makes sense from an intuitive point of view: High volatility stocks produce stronger and longer lasting trends, which can be better exploited by moving averages.

The correlation analysis for crossing levels from 1% to 3.5% produce slightly worse results than the 0.5 crossing level.

Model MACDR2 and Trading Volume

Another interesting question is whether the success rate of model MACDR2 is positively correlated to the trading volume of a stock. The reasoning is that the higher the trading volume, the more technical analysis is used in the trading decision. However, all regression coefficients indicated no significant correlation.

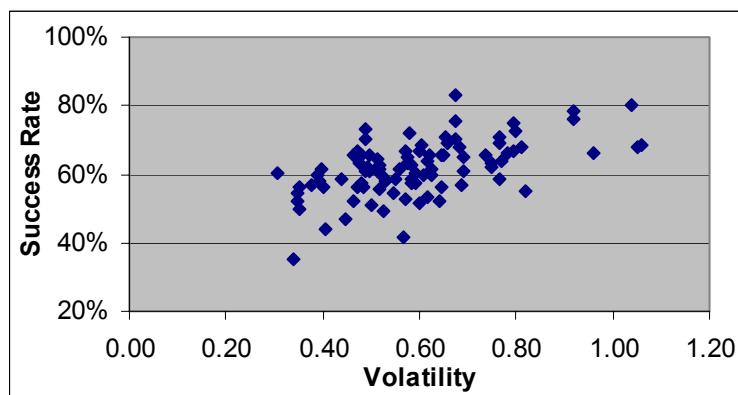


Figure 4: Success rate of model MACDR2, 0.5% crossing level, with respect to volatility; Target gain 3%

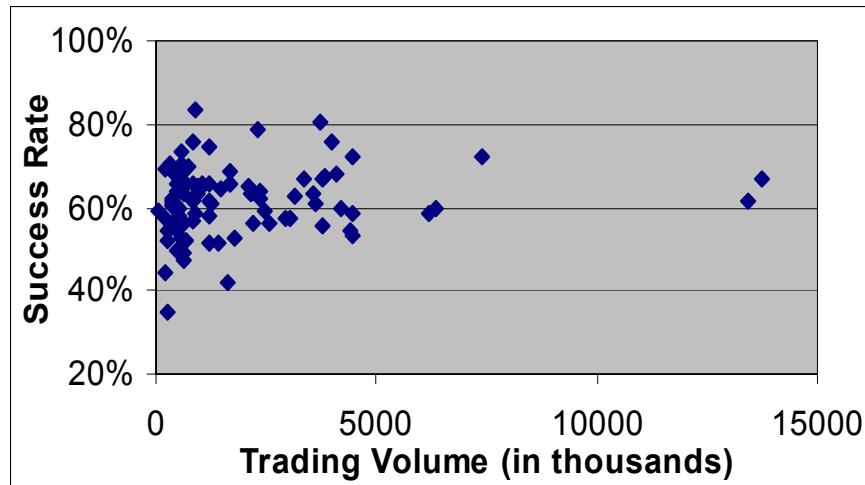


Figure 5: Success rate of model MACDR2 with respect to trading volume; Target gain 3%

Figure 5 confirms that the trading volume theory cannot be supported.

Traditional MACD and Method MACDR2 for Different Moving Average Time Periods

In trading practice, traders usually use the difference between the 26 and 12-day exponential moving average to derive the MACD1 indicator. Then the 9-day moving average of the MACD1 indicator is calculated and called the Signal indicator.

An interesting question is whether moving averages of different time lengths give better trading results regarding the traditional MACD

indicator as well as our method MACDR2. In our study we tested moving averages from 5 days to 100 days, leaving the proportion of 26, 12, and 9 unchanged, rounding to the nearest integer.

Figure 6 shows the results of the different moving averages. The horizontal axis represents the time lengths of the moving average. The numbers on the horizontal axis reflect the longest average. For example, the number 55 represents the average combination 55, 25 and 19.

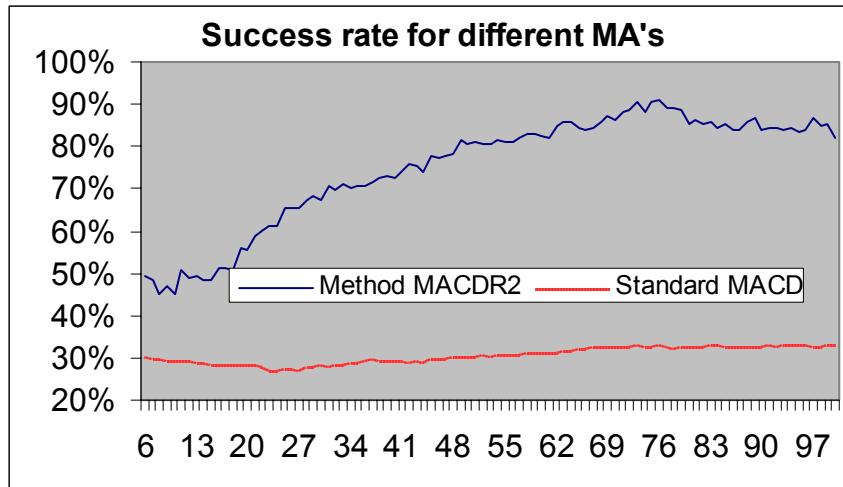


Figure 6: Success rate of the traditional MACD and method MACDR2 for different moving average time periods.

From Figure 6, we can see that the traditional MACD does not improve for different moving averages. The success rate is fairly constant around a disappointing 30% level.

Figure 6 also shows a slightly positive correlation of method MACDR2 (with a 1.5% crossing level) with longer moving averages. The best result is achieved using the moving average combination 73, 34 and 25. Here the success rate is 90.74%.

Model MACDR2 and the Random Walk Hypothesis

In this study, we compared the success rate of method MACDR2 to holding a riskless security, the 10-year Treasury bond, over the 10-year

research period. On the start day of this study, the 10-year Treasury yield was 8.268%. Without reinvesting the coupons, after 10 years, \$1,000 would have increased to $1,000 \times [1 + (0.08268 \times 10)] = \$1,826.80$

The benchmark of holding the underlying asset, the NASDAQ-100 index, results in an average yearly increase of 45.62% over the 10-year study period, since the Nasdaq was at 444.21 points at the beginning and 2470.52 points at the end of the 10-year study period. In dollar terms, \$1,000 invested at the beginning of the study would have increased to $1,000 \times [1 + (0.4562 \times 10)] = \$5,562.00$ excluding reinvestment of the any profit. Holding the NASDAQ-100 can be conveniently achieved by holding the NASDAQ-100 Index Tracking Stock, Symbol QQQ.

The QQQ has a zero dividend yield; therefore, dividends can be neglected in calculating the QQQ increase.

Using daily closing prices, the average profits and losses of method MACDR2 were largely symmetrical. An exact 3% gain or loss of every trade can be achieved by intra-day trading.

This requires high liquidity, which is given, since the QQQ trades on a \$1/64, thus a \$0.01656 minimum bid-offer spread. This minimum spread will soon even narrow to \$0.01 with the use of decimals.

Table 3 summarizes the MACDR2 performance:

Degree of Crossing bigger equal than	10-Year Profit	10-Year Profit incl. a \$5 per trade transaction fee	10-Year Profit incl. a \$5 transaction fee and a max. trading constraint	10-Year Profit incl. \$10 a per trade transaction fee	10-Year Profit incl. a \$10 transaction fee and a max. trading constraint
0.5%	26,962.36	8,627.36	2,035.89	-9,707.64	-454.23
1%	17,590.78	8,440.78	3,024.96	-709.22	534.85
1.5%	10,952.34	6,957.34	4,713.26	2,962.34	2,223.15
2%	11,433.09	7,893.09	5,848.76	4,353.09	3,358.64
2.5%	3,571.24	2,871.24	2,871.24	2,171.24	2,171.24
3%	2,053.40	1,808.40	1,808.40	1,563.40	1,563.40
3.5%	1,590.85	1,465.85	1,465.85	1,340.85	1,340.85

Table 3: Performance of Method MACDR2 including transaction costs and maximum trading constraints

A \$10 per trade fee naturally worsens the MACDR2 performance (column 5) further. Together with the maximum trading constraint (column 6), none of the methods outperform the

NASDAQ-100 and only 3 out of 7 outperform the Treasury bond.

It can be expected that the trading costs will decrease further in the

future². Some brokerage houses provide a yearly trading fee with unlimited trading. However, there is usually a maximum dollar trading balance. At the time of the study (Fall 2000), Merrill Lynch charged a \$1,500 yearly trading fee for unlimited trading. However, if the trading balance increases to over \$150,000, the yearly trading fee increases to 1% of the trading balance. Naturally the decrease of trading costs will increase the relative performance of method MACDR2.

The underlying dollar amount invested at the beginning of the simulation, which is summarized in table 3, is \$1,000. Higher dollar amounts principally increase the relative performance of method 2, since the percentage trading fee decreases. Notably though, the performance including a \$5 trading fee and the maximum trading constraint increases only slightly. A starting amount of \$10,000 leads to a better performance than holding the NASDAQ-100 for the 1.5% and 2% version (with \$1,000 only the 2% version was superior). The same result is achieved for higher starting amounts than \$10,000, both for the trading fee of \$5 and \$10.

One drawback of method MACDR2 is that an investor can be unlucky in the sense that his first trades lead to losses. He can then not reinvest the initial investment amount, as it is

assumed in this study.

4. Conclusion

The popular MACD indicator results in a poor success rate of 32.14% for the Dow 30 stocks and 32.73% for the individually tested NASDAQ-100 stocks over a 10-year period. However, the derived MACDR2 model, which is slightly positively correlated to the volatility of the stock, results in a good, out-of-sample tested, trading performance. The most successful version of the model MACDR2, which exploits only high degrees of crossing of the MACD1 and Signal indicator, results in a success rate of 89.39%. The average profit of the 89.39% successful trades is 6.83%.

Since the holding period of method MACDR2 is on average only several days, the trading results can be enhanced with option trading. The risk-adjusted Sharpe ratio of option trading increases for most levels of implied volatility, which have occurred in the past. However, using the high implied volatilities of April and December 2000, the Sharpe ratio of trading options is lower than the Sharpe ratio of trading the underlying stocks.

Testing different moving averages than the market standard 26, 12 and 9-day average does not improve the trading results of the traditional MACD indicator. However the success rate of method MACDR2 is slightly positively

² For a comparison of trading fees of 35 online-brokers, see www.stockwiz.com/brokers.html

correlated to the time period of the moving average. A 90.74% success rate is achieved for the moving average combination 77, 34 and 25.

Comparing method MACDR2 with a benchmark of holding a riskless asset, the Treasury bond and the underlying asset, the NASDAQ-100, we find that most versions of methods MACR2 can outperform these benchmarks. Therefore, this study provides evidence against the random walk hypothesis. However, when including trading costs and maximum trading constraints, the performance of method MACDR2 weakens significantly.

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