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MOVING AVERAGE TRADING RULES FOR NASDAQ COMPOSITE INDEX

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Abstract: This paper tests a few moving average technical trading rules for the NASDAQ Composite index from 1972 to 2015. Our results indicate that moving average (MA) rules do exhibit strong predictive power for NADSAQ composite index. Can a trader use this predictive to beat the Buy and hold strategy? We show that MA-100 days can, most of the time, make an abnormal profit in the case of NASDAQ composite index by considering both transaction costs and risk. In addition RSI and MACD trading rules have also strong predictive power.

Keywords: moving average, trading rules, abnormal profit, market efficiency, transaction costs

1. Introduction

The Efficient Market Hypothesis (EMH) has provided the foundation of many academic textbooks in finance and investments. The EMH suggests that investors cannot expect to outperform the market consistently. This is because securities prices fully reflect all available information; any new information will be quickly and instantaneously reflected in prices (Fama, 1970). Since securities prices incorporate all known information and new information comes randomly, day-to-day price changes follow a random walk over time, although with a positive drift. A random walk implies any price pattern is accidental and if securities prices follow a random walk, trading rules and other Technical Analysis (TA) methods of predicting securities prices will be useless.

Contrary to the above suggestion, there are many traders using TA principles to predict future prices. TA can be dated back hundreds of years ago. According to historical records, a great Japanese rice trader by the name of Homma Munehisa (1724-1803) who fathered candlestick charting at today’s value, would have made over $100 billion in profits and been considered as the greatest trader in history of financial markets. In the U.S., technical analysis was initiated by Charles Dow (1851-1902), the founder of Wall Street Journal and Dow Chemical. Today many traders still follow his Dow Theory for buy and sell signals and the Dow Jones Industrial Index still serves as one of the most important reflections for the U.S. stock market.

The development of technical analysis is based upon three assumptions: 1) the market discounts everything. In other words, all of financial positions of a company are reflected in its stock price; 2) price moves in trends; that is, a trend line will be of tremendous help to predict the future prices. Early detection of a trend is essential to the success of TA. One of the most important trend determining techniques is the use of moving average (MA) employed in this paper; and 3) history tends to repeat itself; this implies traders and investors will react in same way to the same conditions which will create opportunity for profitable trading. As Meyers (2002) states: “Technicians record, usually in chart form, historical price and volume activity and deduce from that pictured history the probable future trend of prices.”

The purpose of this paper is twofold. First, we examine whether moving average (MA) trading rules have predictive power in the NASDAQ composite Index (NASDAQ); and secondly, if MA trading rules do exhibit predictive power, could a trader design a strategy to beat the profitability of the buy and hold (B&H) strategy, considering transaction costs and risk? Our results indicate that MA trading rules do exhibit strong predictive power for NADSAQ composite index. A trader employing MA-100 trading rule could most of the time make an abnormal profit even considering both transaction costs and risk. We also develop two strategies associated with MA-100 for different risk-tolerance traders to beat handsomely the buy-and-hold NASDAQ strategy. In addition we show that the RSI and MACD trading rules have also strong predictive power.

The remainder of this article is organized as the following. Section 2 details some of the relevant literature. Section 3 describes the data and methodology. The empirical results of various moving average trading rules are exhibited in Section 4. Section 5 compares different strategies to locate the most profitable strategies to beat the buy-and-hold strategy considering transaction costs and market risk. The final section provides concluding remarks.

2. Literature Review

It is possible to trace the history of TA back to 17th century, an Amsterdam trader, poet, and philosopher, Joseph Penso de la Vega. However as we have mentioned above, the fathers of modern TA are the Japanese rice trader, Homma Munehisa (candlestick charting) and Charles Dow the founder of Wall Street Journal and Dow Theory. In the 1920s and 1930s, Richard W. Schabacker published several books which continued the work of Charles Dow and William Peter Hamilton in their books Stock Market Theory and Practice and Technical Market Analysis. In 1948 Robert D. Edwards and John Magee published Technical Analysis of Stock Trends, which is widely considered, even today, to be one of the seminal works of the TA. Other pioneers contributed to TA including Ralph Elliot (the Elliot wave principles) and William Gann (the Gann angles and arcs). Most technicians were Wall Street traders and most finance professors were believer of EMH. In early 1970s and 1980s, the Random Walk Hypothesis and its close relative EMH had become icons of modern financial economics that continue to have many followers in academic circles as well as professional fund manager in today’s world. As Lo and MacKinley (1990) point out, even after three decades of research and thousands of journal articles, finance professors and economists have not yet reached a conclusion about whether financial markets are efficient or not. Early well-known empirical studies supported weak form market efficiency, implying that a trader cannot use past prices to forecast future prices. See for example Larson (1960), Cowles (1960), Granger and Morgenstern (1963), Mandelbrot (1963), Alexander (1964), Fama (1965), Fama and Blume (1966), Van Horn and Parker (1967), and Jensen and Benington (1970).

However since the mid-1980s, technical trading has enjoyed a renaissance both on Wall Street and in academic circles. Several papers have questioned the validity of EMH by demonstrating that simple technical trading strategies possess significant power to predict future security prices. The cornerstones of this renaissance in technical analysis were articles by Sweeney (1986), Lukac et al. (1988), and Brock, Lakonishok and LeBaron (1992, BLL hereafter). Sweeney (1986) applies some filter rules for ten currencies and find that various filters were profitable in more than 80 percent of the cases. Lukac et al. (1988) find that moving average rules statistically beat the buy and hold strategy. In 1992 a seminal paper by BBL analyzes moving averages and trading rules on the Dow Jones Industrial Index for a period of 89 years from 1897 to 1985. They use various short and long moving averages of prices to generate buy and sell signals. They point out that ‘all buy-sell differences are positive and the t-tests for these differences are highly significant…’ and they go on to conclude that their ‘results are consistent with technical rules having predictive power’.

Park and Irwin (2007) provide an excellent survey of technical trading rules by differentiating the early studies from the modern studies; they conclude that early studies do not support the predictive power of TA for equity market, and 56 out of a total 95 modern studies support profitable trading rules. The bulk of modern studies suggest that trading rules, especially the moving average rules, exhibit predictive power. However, whether applying those trading rules to obtain abnormal profits when including transaction costs and risk is not clear for most indexes

3. Data and Methodology

In this paper, we employ a simple technical analysis approach to test the predictive power for Nasdaq Composite index. The exchange traded fund (ETF) that mimics NASDAQ composite index has been listed on the NASDAQ National Market and has been traded since October 1, 2003 (ticker symbol: oneq).

We use Datastream’s daily closing price of the NASDAQ composite index over the period of 1/3/1972 to 10/14/2015 and define the daily returns as changes in logarithms of the each index price. Although estimating the return this way does not consider dividend yield, Mills and Coutts (1995) review the literatures regarding dividends exclusion and conclude that any bias in the results due to dividend exclusion will be minimal. This conclusion is also supported by Draper and Paudyal (1997). The proxy interest data (i.e. money market rate) used in this study is from Datastream’s daily Federal Fund rate. In order to get the daily interest return, we follow Lucke (2002) by dividing the annual rates by 260.

The art of technical analysis – in fact it is an art to identify trend changes at an early stage and to maintain an investment position until the weight of evidence indicates that the trend has been changed (Pring, 1991). As Kirkpatrick and Dahlquist (2015) point out, one of the most successful techniques of identifying and profiting trends is the use of moving averages. According to MA rules, buy (sell) signals are generated when a short-term moving average exceeds (is less than) the long-term moving average by a specified percentage. In this study we use the long-term moving averages of 20, 50, 100, 150 and 200 days. As for the short-term moving average, like the BLL study, we use 1 day (the raw price) moving average. Thus, a buy signal is emitted when the index price level breaks the long MA from below and a sell signal is emitted when the index level breaks the long MA from above.

We define Pt as the short-term moving average or the raw index level at time t, and define the long-term moving average of M-day at time t as:

$$MA_t(M) = \frac{1}{M}\sum_{i=0}^{M-1} P_{t-i}\,. \tag{1}$$

An investor/trader who follows MA trading rules could presumably estimate the index price that would trigger the buy and sell signal just before the day's close and initiate a conditional limit order at the close of the market to perform various trading rules. For example a trader that has been out of the market following a trading rule based on MA50 (if P > MA50, in the market and if P ≤ MA50 then out of the market) could have the following conditional limit order at the close of the day: If the price index is above previous close of MA50, then buy market on close (MOC). Therefore the trader will be in the market the next day by buying the index at the closing limit price (i.e. next day will be a buy day). The next day's return will be the change in logarithms of the index level. The same reasoning holds if the trader has been in the market, sell the index MOC if price is below previous close of MA50 (i.e. next day will be a sell day). The next day's return will be the change in logarithms of the index level. If the conditional limit prices are not filled, then the trader will not switch position. The trader is either in the market "buy" days or out of the market "sell" days, again the sell days mean the trader is out of the market and not shorting the market.

We define mean buy and mean sell day returns as follows:

$$\mu_b = \frac{1}{n_b}\sum R_b \tag{2}$$

$$\mu_s = \frac{1}{n_s}\sum R_s \tag{3}$$

where, R_b and R_s are daily returns of buy and sell days; n_b and n_s are the total number of buy and sell days respectively. We will test whether the returns of any moving average trading rules are greater than a B&H strategy and whether the mean buy is different from the mean sell. The null and alternative hypotheses are expressed in Table 1:

Table 1: Test Hypotheses

	Test One	Test Two	Test Three
Null: H_0	$\mu_b - \mu_h = 0$	$\mu_s - \mu_h = 0$	$\mu_b - \mu_s = 0$
Alternative: H_a	$\mu_b - \mu_h \neq 0$	$\mu_s - \mu_h \neq 0$	$\mu_b - \mu_s \neq 0$

where μ_h is the mean of the B&H strategy. Following Kwon and Kish (2002), the test statistic for the Test is:

$$t = \frac{\mu_b - \mu_s}{\sqrt{(\sigma_b^2 / n_b) - (\sigma_s^2 / n_s)}}\,, \tag{4}$$

where μ represents the mean returns, σ^2 is the estimated variance, and n is the number of observations in each situation. Statistically significant differences in buy-sell day index returns implies the effectiveness of the MA rules to forecast equity returns, this is the same procedure used by BBL. The above formula is also used for Test One and Test Two by replacing the appropriate variables in the t-statistic formula.

4. Empirical Results

In Table 2, we exhibit the summary statistics of daily returns for NASDAQ index in the entire 43.875 years with four sub-periods for comparison. For the entire period (01/72~10/15), the average daily return is 0.033% with a standard deviation of 1.23 over 11423 observations or days. The t-statistics for the mean returns of B&H in NASDAQ is 2.84. At the 5 percent confidence level for large numbers of observations, compared with the critical t-value 1.96 for two-tailed test, the unconditional means of NASDAQ for the entire period are significantly different from zero. The skewness implies that return distributions are almost symmetric for NASDAQ index. The Kurtosis is higher than 3, implying that the return distributions may not be normal, and the Jarque-Bera test rejects normality of returns in the entire period and all four sub-periods. All of the first and second order autocorrelations are low except for the first and second sub-periods.

Table 2: Summary Statistics of Returns: NASDAQ Composite Index

NASDAQ Composite Index								
Period	**Mean %**	**SD %**	**Skewness**	**Kurtosis**	$\rho 1$	$\rho 2$	*JB*	*n*
01/72 – 10/15	0.033%	1.23%	-0.29	10.08	0.05	-0.01	24046	11423
01/72 – 12/84	0.023%	0.76%	-0.77	3.91	0.32	0.08	453	3391
01/85 – 12/94	0.043%	0.86%	-2.28	30.79	0.26	0.05	86191	2609
01/95 – 12/04	0.041%	1.80%	0.01	4.05	0.00	-0.01	120	2610
01/05 – 10/15	0.028%	1.33%	-0.25	7.85	-0.07	-0.01	2788	2813

Note: SD = Standard Deviation; JB = Jacque Bra; critical value = 6; $\rho 1$ & $\rho 2$ = first and second order return correlations; n = total number of days in the period.

Table 3 summarizes the results of various moving average (MA) trading rules for the NASDAQ index. For each MA rule, we report mean buy returns, mean sell returns, the mean buy minus sell returns, standard deviations of returns on buy and sell days, total number of buy and sell days, and the number of signals generated. The numbers in the parentheses are the t-statistics defined in Equation *(4)* to test the difference of the mean buy and mean sell from the unconditional mean, and buy-sell from zero. For example, the first row of NASDAQ Composite Index shows the results of MA-20 trading rule. The trader will be in the market (buy days) if the index level is greater than MA20 and out of the market (sell days) if the index level is less than or equal to MA-20. Similarly, the other rows report the results of other MA-days trading rules.

Table 3: Statistical Results for Moving Average Rules

NASDAQ Composite Index								
Rules	**Buy**	**Sell**	**Buy-Sell**	***SDb***	***SDs***	n_b	n_s	**No. of Signals**
MA-20	0.00091 (3.60)*	-0.00054 (-3.46)*	0.00145 (5.76)*	0.00966	0.01539	6847	4576	1090
MA-50	0.00081 (3.01)*	-0.00047 (-2.98)*	0.00128 (4.82)*	0.00949	0.01583	7101	4322	605
MA-100	0.00068 (2.22)*	-0.00030 (-2.23)*	0.00098 (3.53)*	0.00929	0.01630	7300	4123	381
MA-150	0.00055 (1.45)	-0.00013 (-1.54)	0.00068 (2.33)*	0.00927	0.01681	7639	3784	347
MA-200	0.00054 (-0.20)	-0.00013 (0.23)	0.00067 (-0.31)	0.00948	0.01688	7835	3588	273

Moving average trading results for daily data from 1972-2015. n_b and n_s are the number of buy and sell days, SD_b and SD_s are standard deviation of buy and sell days respectively. The numbers in the parentheses are the t-statistics testing the difference of the mean buy and mean sell from the unconditional 1-day mean, and buy-sell from zero. Numbers marked with asterisks are significant at the 5% level for a two-tailed test, $t_{crit., 0.05}$ =1.96.

The testing results of significance in Table 3 are very strong for NASDAQ. The mean buy and sell returns are shown in Columns 2 and 3. For MA20, MA50, and MA100 in NASDAQ, the mean buy returns are all positive with significant t-statistic and the mean sell returns are all negative with significant t-statistic. All the buy minus sell differences (Column 4) are positive and the t-test statistics are highly significant to reject the null hypothesis of equality with zero, except for MA-200. Therefore, the four out of five MA trading rules, MA20, MA50, MA100 and MA150 have predictive power in the NASDAQ Composite Index.

It is interesting to note that the standard deviations for buy days are always smaller than those for sell days in Columns 5 and 6. This implies that the down markets are more volatile than the up markets. Columns 7 and 8 report the number of buys and sells for various rules. For example when applying MA20 trading rule for NASDAQ, 60% of the days we are in the market (buy days) and 40% of the days out of the market (sell days). Finally the last column reports the number of signals for in and out of the market, as the MA days increases the number of in and out of the market decreases. It is also noteworthy to point out the negative returns for sell days is problematic for the proponents of EMH. As BLL indicates, these returns cannot be explained by seasonality since they are based approximately on 40% of all trading days. This predictability of returns can reflect either (1) changes in expected returns generated from an equilibrium model, or (2) market inefficiency. Although changes in expected returns are possible, it is hard to imagine an equilibrium model that predicts negative returns over such a large fraction of trading days.

The results in Table 3 indicate that moving average rules do indeed have predictive power for NASDAQ and can discern recurring-price patterns for profitable trading. Given the predictive power of MA rules, the next section discuss how can we design various trading strategies to beat the B&H strategy considering both transaction costs and market risk.

5. Trading Strategies

Now that we have confirmed the predictive power of MA rules for NASDAQ, we investigate whether it is possible to design various trading strategies for MA rules to beat the B&H strategy considering both transaction costs and risk. For each MA trading rule, the profitability will be varied with the position a trader takes when the rule emits sell signals. For example, if a trader does not invest in any alternative on the sell days (out of market), then his or her return on the sell days will be zero. Then the trader's mean return can be counted as simple as $(n_b/n)*\mu_b + (n_s/n)*0$. If a trader chooses to invest in the money market on the sell days, then the trader's mean return will include the interest earnings at money market rate on those sell days.

In this study, following Metghalchi et al. (2015), we consider a total of four strategies as the following:

Strategy 1 — The trader will be in the stock market when MA rules emit buy signals and be in the money market when a MA rules emit sell signals (long/money).

Strategy 2 — The trader will be in the stock market when MA rules emit buy signals and short the market when the rules emit sell signals (long/short).

Strategy 3 — The trader will borrow at the money market rate and double stock investment when trading rules emit buy signals and be in the money market when trading rules emit sell signals (leverage/money).

Strategy 4 — The trader will borrow at the money market rate and double stock investment when trading rules emit buy signals; short the market when the trading rules emit sell signals (leverage/short). Note that the total return on buy days for the leverage strategy is $TR_t = 2R_t - M_t$, where R_t is the index return on day t and M_t is the daily money market rate.

For each strategy, we estimate the daily return then subtract it from the daily return of B&H strategy to get the daily difference return. To test whether the average daily difference (*ddif*) is greater than zero or not, we express the null and alternative hypotheses as:

$$H_0:\ ddif \leq 0$$

$$H_a:\ ddif > 0$$

The t-statistic for the above test is:

$$t = \frac{\mu(ddif)}{\sqrt{\sigma^2(ddif)/n}}\ , \qquad (5)$$

where μ (*ddif*) is the average daily difference of returns of each strategy over the B&H strategy and σ^2(*ddif*) is the variance of daily difference returns, and n is the total number of days. Table 4 reports the results of the above six strategies for MA rules.

Table 4 shows the strong results with positive daily difference returns and significant *t*-statistics. At first glance, MA20 and MA50 rules with *Strategies 3, 4* are the most profitable rules and strategies. If market risk and transaction costs are not considered, then the best strategy would be to apply MA20 rule using *Strategy 4*, an extra return of 0.085% per day over the B&H strategy.

Table 4: Trading Strategies of MA Rules in NASDAQ

	Strategy 1	Strategy 2	Strategy 3	Strategy 4
	$\mu(ddif)$	$\mu(ddif)$	$\mu(ddif)$	$\mu(ddif)$
MA-20	0.00030 (3.33)*	0.00043 (2.36)*	0.00072 (6.31)*	0.00085 (4.27)*
MA-50	0.00026 (2.89)*	0.00035 (1.94)*	0.00064 (5.59)*	0.00073 (3.65)*
MA-100	0.00019 (2.09)*	0.00021 (1.16)	0.0005 (4.33)*	0.00052 (2.59)*
MA-150	0.00012 (1.35)	0.00009 (0.48)	0.00036 (3.13)*	0.00032 (1.60)
MA-200	0.00012 (1.35)	0.00009 (0.48)	0.00036 (3.13)*	0.00032 (1.60)

$\mu(ddif)$ is the average of daily difference between the return of each strategy and the buy-and-hold strategy. The numbers in the parentheses are the *t*-statistics testing whether the average daily difference is greater than zero. Asterisks imply significant at the 5 percent level or less for one-tail test, $t_{crit., 0.05}$ =1.645.

However, we must consider risk and transaction costs of each strategy in order to choose the best rule/strategy. Table 5 reports the one way "break-even" transaction costs and the risk of various MA rules for the above four strategies. The one-way break-even transaction cost (BEC) eliminates the extra return from MA trading rules. Following Bessembinder and Chan (1995), we estimate the one way BEC by adding the daily excess returns (Beyond B&H) produced by each trading rule and strategy over the 11423 days and then divide it by the number of trades over the entire period. Since Strategies 2 and 4 imply shorting the NASDAQ index, we divide the sum of the daily excess return by 2 times the number of trades. We also assume that investing in a money market does not incur any transaction cost. The estimation of risk is the standard deviation of daily returns of each strategy which should be compared with the daily standard deviation of B&H strategy of 1.23 % in Table 2 for the entire period.

Table 5 provides BEC and risk of each trading rule and various strategies; the first number in each cell is the BEC and the second number is risk, both in percent. Strategy 1 has an average risk of 0.76 % much lower than the B&H risk of 1.23 % of Table 2. The risk of Strategy 2 is similar to the risk of the B&H strategy. Finally, the average risk of the Strategies 3 and 4 are 1.51% and 1.80% respectively, both higher than the risk of B&H strategy. In comparison, Strategy 1 is superior to Strategies 2 due to its higher BEC and lower risk. The risk and return trade-off implies that if a trader prefers a lower-than-market risk, then Strategy 1 in combination with MA-100 or MA-150 or MA-200 would be the best trading rules with BEC of 0.22, 0.24, and 0.29 percent. On the other hand, if a trader has a little higher risk tolerance, then Strategy 3 is superior to Strategies 4, since strategy 3 implies lower risk and higher BEC than Strategies 4. Strategy 3 with either MA rules of 100, 150, or 200 days will provide profitable trading if transaction cost of trading NASDAQ composite ETF is less than 0.29 %. In conclusion, MA-100, MA-150, and MA-200 associated with Strategies 1 and 3 serve as the most profitable choices for traders.

Table 5: Break-Even Costs and Risk of Various Strategies

	Strategy 1	Strategy 2	Strategy 3	Strategy 4
MA-20	0.10/0.75	0.09/1.23	0.15/1.49	0.11/1.78
MA-50	0.15/0.75	0.12/1.23	0.20/1.50	0.15/1.79
MA-100	0.22/0.74	0.17/1.23	0.29/1.49	0.21/1.78
MA-150	0.24/0.76	0.19/1.23	0.33/1.52	0.23/1.80
MA-200	0.29/0.79	0.22/1.23	0.38/1.57	0.26/1.83

The break-even cost (BEC) estimated by dividing total daily excess returns into total number of trades over the entire period from 1972-2015. Risk is the standard deviation of daily returns. In each cell the first number is the BEC in percent and the second number is risk in percent. Each cell shows (BEC/Risk).

To test the robustness of results, we divide the entire sample into four sub-periods and provide the estimated BECs for Strategies 1 and 3 for MA-100, MA-150, and MA-200 in Table 6. Table 6 presents the risk and BECs of our best three rules for four sub-periods. The risks (standard deviation of returns) of the B&H strategy are 0.761 %, 0.856 %, 1.795% and 1.332 % for four sub-periods respectively. The BECs are estimated the same way, by dividing total excess return over the B&H strategy into the total number of trades in each sub-period.

Noted in Table 6, the BEC are relatively high in the first three sub-periods for both Strategies 1 and 3. Compared with the risk of B&H in each period, Strategy 1 again has a lower risk in each sub-period with high BEC in the first three sub-periods. Strategy 3 has a bit higher risk in each sub-period than B&H but has very high BEC implying strong possibility of profitable trading. A trader with a bit more risk tolerance than B&H would adopt MA-100 with combination of Strategy 3 to gain higher BEC in each sub-period, including the fourth sub-period. For risk-averse choice, a trader could apply MA-100 with Strategy 1 and gain very well in the first 3 sub-periods but would lose not much (since BEC is a small negative number) in the fourth sub-period. Our findings also partially echo Feng et al (2013) to indicate that MA trading rules have not been very successful recently, since the publication of BLL.

In order to see whether other well-known trading rules can do as well as moving average rules, we apply two addition popular indicators to NASDAQ composite index. The Relative Strength Index (RSI) indicator, which measures the velocity of directional movement by providing the internal strength of a single security or index, was created by Wells Wilder (1978). Wilder suggests using 14 days for estimating the RSI's value which ranges from 0 to 100. In this study we use two variants of RSI trading as follow:

I. In the market if RSI >50;
Out of the market if RSI ≤ 50.

II. Many traders believe if RSI is above 85 it implies that the market is overbought and if it is below 15, then the market is oversold. Thus RSI model 2's rules are as follow:

In the market if: 50 ≤ RSI ≤ 85 or if: RSI ≤ 15;
Out of the market if: 15 < RSI <50 or if RSI > 85.

Table 6: Break-Even Costs and Risk of Various Strategies

Strategy 1						
	MA-100		MA-150		MA-200	
Sub-Period	**BEC %**	**RISK %**	**BEC %**	**RISK %**	**BEC %**	**RISK %**
1/72 – 12/84	1.63	0.48	2.46	0.50	1.72	0.51
1/85 – 12/94	0.89	0.56	0.67	0.56	0.39	0.57
1/95 – 12/04	0.34	1.06	0.20	1.10	0.51	1.16
1/05 – 10/15	-0.09	0.78	-0.35	0.79	-0.32	0.81
Strategy 3						
Sub-Period	**BEC %**	**RISK %**	**BEC %**	**RISK %**	**BEC %**	**RISK %**
1/72 -12/84	2.74	0.99	4.1	1.00	2.75	1.02
1/85 – 12/94	2.54	1.11	2.26	1.13	1.74	1.14
1/95 – 12/04	1.27	2.13	1.04	2.19	2.01	2.31
1/05 – 10/15	0.34	1.56	-0.24	1.59	0.04	1.61

Results for four sub-periods. BEC is the break-even cost, estimated by dividing total daily excess returns for each sub-period into total number of trades in that sub-period. Risk is the standard deviation of daily returns in each sub-period.

The second popular indicator allied to NASDAQ Composite is the Histogram based on Gerald Appel's (1980) Moving Average Convergence Divergence (MACD), Stochastic. MACD is the difference between two exponential moving averages (EMA). We follow the Appel's recommendation and use 26 and 12 day EMAs. A 9-period EMA of the MACD (the signal line) is then plotted on top of the MACD. The trading rule is as follow: in the market if MACD is above the signal line and out of the market if MACD is below signal line. In Table 7 we present the results for the above three models, two based on RSI and on one MACD rules.

Table 7: Statistical Results for RSI and MACD Rules

NASDAQ Composite Index								
Rules	**Buy**	**Sell**	**Buy-Sell**	SD_b	SD_s	n_b	n_s	**No. of Signals**
RSI-1	0.00091 (3.64)*	-0.00219 (-10.04)*	0.00310 (12.45)*	0.00938	0.01473	7029	4394	983
RSI-2	0.00088 (3.37)*	-0.00050 (-3.23)*	0.00138 (5.38)*	0.00964	0.01540	6842	4581	1113
MACD	0.00065 (1.76)	-0.00130 (-8.27)*	0.00195 (9.17)*	0.01065	0.01202	5789	6534	859

Results are for daily data from 1972-2015. n_b and n_s are the number of buy and sell days, SD_b and SD_s are standard deviation of buy and sell days respectively. The numbers in the parentheses are the t-statistics testing the difference of the mean buy and mean sell from the unconditional 1-day mean, and buy-sell from zero. Numbers marked with asterisks are significant at the 5% level for a two-tailed test, $t_{crit., 0.05}$ =1.96.

The results of Table 7 strongly support the predictive power of RSI and MACD trading rules; all buy minus sell t-statistics are highly significant rejecting the hypothesis that the mean buy days is equal to the mean sell days. In Table 8 we report the average buy minus sell days for each sub-period with their corresponding t-statistics.

Table 8: Mean buy minus mean sell for each sub-period

	Sub-Period 1	Sub-Period 2	Sub-Period 3	Sub-Period 4
RSI 1	(12.73)*	(7.72)*	(5.74)*	(3.02)*
RSI 2	(5.38)*	(4.28)*	(2.48)*	(-0.97)
MACD	(9.47)*	(6.32)*	(3.34)*	(2.80)*

Mean buy minus mean sells are the difference of average buy days minus average of sell days for each sub-period. The numbers in the parentheses are the t-statistics testing the difference of buy-sell from zero. Numbers marked with asterisks are significant at the 5% level for a two-tailed test, $t_{crit., 0.05}$ =1.96.

Again, Table 8 concludes a very strong predictive power of technical trading. All except one buy minus sell averages are highly significant rejecting the equality of mean buy days with mean sell days. This conclusion does not support the efficiency of NASDAQ composite index.

4. Conclusion

In this paper, we investigate a few moving average trading rules for the NASDAQ Composite index over the period of 1/3/1972 to 10/14/2015. Overall our results strongly support the predictive power of MA trading rules for NASDAQ. Almost all the buy-sell differences are significantly positive to reject the null hypothesis of equality of buy days returns with sell days returns for NASDAQ. For NASDAQ, the t-statistics for most buy and most sell are significant, rejecting the null hypothesis that the mean buy and sell returns equal to the mean of B&H returns. Therefore, we can conclude that MA rules have predictive power for NADAQ composite index.

To investigate the most profitable strategies for MA rules for NASDAQ when considering both transaction costs and risk, we design a total of 4 strategies to test the significance and robustness in profitability. There are two driftnet risk tolerance strategies found to be very profitable when using MA-100 in NASDAQ. For risk-averse investors, Strategy 1, in which a trader will be in NASDAQ when MA-100 emits buy signals and be in the money market when MA-100 emits sell signals, is the choice to beat the B&H strategy for entire period (BEC of 0.22 %, and a risk lower than B&H) and 3 out of 4 sub-periods with very high BECs. For a more risk-taker trader, applying MA-100 with Strategy 3 (i.e. a bit more risk than B&H) leveraging at money market rate for buy days and being in the money market for sell days, can beat handsomely the B&H for the entire period and each sub-period. Finally we apply two very popular indicators (RSI & MACD) to NASDAQ composite index and find that both also have very strong predictive power for entire period and each sub-period. We would note that both RSI and MACD trading rules imply more in and out of the market than MA 100, therefore traders with higher transaction costs should be careful to apply these trading rules.

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