Performance of Moving Average Investment Timing Strategy in UK Stock Market: Individual Stocks versus Portfolios

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Abstract: *This paper aims to test whether moving average (MA) investment timing strategy is applicable on individual stocks, portfolios formed from these stocks, or both. Moreover, our objective is to compare the performance of MA strategy with a buy-and-hold strategy. The data on individual stocks listed on London Stock Exchange, United Kingdom (UK) is collected over the period starting from December 31, 1999, through February 29, 2016. For the same period, we use daily values of UK-DS Market-PRICE INDEX and 1-Month Treasury bill rate. The paper follows Han et al. (2013) to peruse our investigation. The study applies both MA and buy-and-hold strategies to individual stocks and portfolios sorted by volatility. Since most results are found insignificant, no evidence is found to support that one strategy is better than the other when applied to individual stocks. However, trading behavior and success ratios across groups provide mixed results, hinting slightly towards the failure of MA strategy. The pervasive noise in daily stock return data is the reason why MA strategy consistently produces insignificant results. Moreover, when applied to volatility-sorted portfolios, MA strategy substantially beats buy-and-hold strategy by yielding higher average return and risk-adjusted returns, lower standard deviations, large-and-positive skewness and Sharpe ratios, and much success ratios across portfolios. Both for individual stocks and portfolios, dynamics of returns and especially trading behavior suggest that the performance of MA strategy decreases with rising lag lengths, meaning MA signal weakens for a longer history.*

Keywords*: Individual Stocks, Higher Yields, and Sharpe Ratio.*

JEL Classification*: G10, G11and D53*

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Literature Review

Historically, stock price prediction has received an enormous amount of attention among investors, practitioners, and academicians. Broadly, two classes of analyses have been used for predicting stock prices. These are commonly known as fundamental and technical analyses. Fundamental analysis uses intrinsic properties of an asset, specifically stock, to estimate future price or intrinsic value. On the contrary, in technical analysis historical data of prices is used to drive signals about future prices. Lately, nevertheless, technical trading rules have been commonly used by investors and financial analysts to make investment decisions (Neely, 1997; Taylor and Allen (1992)). More recently, however, (Han, Zhou, & Zhu, 2016) find results that favor the persistent profitability of the MA trading rule. Zhou and Zhu (2013) documents as MA follows the trend. It is further expected to be high profitability in high IU stocks when there is amore extended price continuation. Metghalchi, Marcucci, and Chang (2012) accept that MA scan forecast. Shintani, Yabu, and Nagakura (2012) point out that MA signals are helpful for investment over a longer time horizon.

On the other hand, numerous studies provide either mixed or reverse evidence. For instance, (Allen & Karjalainen, 1999) establish that, for US stock market, the technical trading strategy does not perform better than buy-and-hold strategy even after accounting for trading costs. Sullivan, Timmermann, and White (1999) examine US futures market and conclude that, after making snooping bias adjustment, there is no clue supporting the profitability of technical analysis. Hoffmann and Shefrin (2014) find that investors who apply technical analysis as their primary strategy in options trading are biased towards short-term speculative trading decisions that are sub-optimal in the long run. Similarly, studying futures markets, (Roberts, 2005) finds no evidence to support the profitability of technical trading rules. Lukac and Brorsen (1990) point out that the returns of technical trading rules are leptokurtic and exhibit positive skewness. The study also reports that the historical applications of t-test for the returns produced by technical trading rules can be biased.

It is worth considering that MA is most popular among a range of technical analysis rules available. Therefore, some literature primarily focuses on moving average; Such as (Hudson, Dempsey, & Keasey, 1996)show that technical analysis rules (especially the MAs) do not perform superior to buy-and-hold strategy when trading is costly; though these rules have predictive power.Wei, Cheng, and Wu (2014) comment that MAs are the trading rules that are most widely known and used by practitioners and financial traders in the markets because MA methods are easily understandable.Brock, Lakonishok, and LeBaron (1992) further examine the application of the MA timing strategy on Dow–Jones Industrial Average and conclude that MA strategy outperforms buy-and-hold strategy. Mills (1997) also demonstrates similar finding while applying the strategy to FT-30 Index. Kwon and Kish (2002) list down the same results for New York Stock Exchange (NYSE).

More recently, (Han, Yang, & Zhou, 2013) apply the moving average (MA) timing strategy in US stock market. The main findings of the study are, MA strategy performs significantly better than buy-and-hold strategy when applied to volatility decile groups. Further, it produces significant average and excess returns. Moreover, these returns also hold for when MA is calculated for more considerable lag lengths. Finally, the excess returns are thus produced sufficiently cover the transaction costs.
This study primarily replicates the research carried out by (Han et al., 2013) while simplifying, and to some extent differentiating, itself in the following ways. First, it studies the application of MA strategy in UK stock market. Second, it considers five quantile groups of individual stocks rather than portfolios. The groups are sorted based on the volatility of individual stocks. Third, it utilizes Capital Asset Pricing Model (CAPM) solely to test for abnormal returns. Fourth, it confirms the robustness of results by using only two ways, alternative lag lengths, and trading behaviors. Finally, it compares the results of individual stocks with that of portfolios.
Overarching the core aim of the study is to explore either moving average (MA) investment timing strategy is applicable on individual stocks or portfolios, for the stocks listed on the London Stock Exchange. Furthermore, our objective is to compare the performance of MA strategy with a buy-and-hold strategy. The following section explains the material and methods which contains the discussion regarding the nature and sources of data and the econometric model's output as well. We conclude the study in the last section under the conclusion head.

Material and Methods

We collect stock price data of 1,565 stocks listed on London Stock Exchange, United Kingdom (UK) from December 31, 1999, to February 29, 2016 (4,217 days). Daily values of UK-DS Market - PRICE INDEX and 1-Month Treasury Security rate are also downloaded for the same period. The data downloaded from Thomson Reuters' DataStream. Risk-free rate and market index data are free from missing values. However, since stock price data does have missing values, so we have to replace such values by not available (NA).

Initially, we calculate the daily returns for each stock. These are the returns under the buy-and-hold strategy. As part of the cleaning process, we replace all returns greater than 300%with NA before moving further. Then for every day, following

(Brock et al., 1992) and (Han et al., 2013), a 10-day moving average (MA) price, $A_{jt,L}$ of each stock is calculated by using the stock prices (P_t) of previous ten days. The MA price formula is given as follows;

$$A_{jt,L} = \frac{P_{jt-(L-1)} + P_{jt-(L-2)} + ... + P_{jt-1} + P_{jt}}{L}, \tag{1}$$

where t = a particular day,

L= the lag lengths which is 10 in the first case,

J = number of stocks; so, j = 1,…,1565.

It is quite simple to apply MA strategy once MA prices are obtained. MA strategy is based on the following notion: on a day, if yesterday's market price (P_t) is higher than yesterday's moving average price ($A_{jt,L}$), invest in the market today; otherwise, invest in the 1-month T-bill today. Mathematically, MA strategy can be expressed as

$$\tilde{R}_{jt,L} = \begin{cases} R_{jt}, & \textit{if } P_{jt-1} > A_{jt-1,L}; \\ r_{ft} & \text{otherwise.} \end{cases} \tag{2}$$

Where $R_{j,t}$ = return on a stock, j , under buy-and-hold strategy

t = a particular day

r_{ft}= the daily 1-month T-bill rate on day t.

$R_{jt,L}$= MA return on a particular day, for a particular stock, and for a particular lag length which is 10 in this case.

MAG is defined as the difference between MA and buy-and-hold returns. Once we have MA returns, MAGs can be calculated in the following way;

$$MAG_{jt,L} = \tilde{R}_{jt,L} - R_{jt}. \tag{3}$$

Note that MAGs measure the performance of MA strategy relative to buy-and-hold strategy. The last portion of Table 1 also reports the success ratio of MA strategy. The idea of success ratio can be described as follow. On a particular day, if MA return is equal to the maximum of either buy-and-hold or risk-free return of that day, the day is considered a success-day; otherwise, it is regarded as a failure-day. Finally, the ratio of all success-days to total trading days available is reported as success ratio.

Further, to assess the risk-adjusted performance of MAGs, We apply CAPM regression between MAG returns and daily excess returns on the market, $r_{MKT,t}$, Famaand French (1993) Which can be expressed as,

$$MAG_{jt,L} = \alpha_j + \beta_{j,MKT} r_{MKT_t} + \varepsilon_{jt}, \quad \mathrm{j} = 1, \ldots, 1{,}565. \tag{4}$$

Where α_j, $\beta_{j,MKT}$ are the alpha(risk-adjusted return) and beta on for each stock. Robustness of results is checked by repeating some steps of the methodology mentioned above. For instance, average returns and alphas are calculated in a similar way but with alternative lag lengths. Alternatively, we test MA strategy for 20-day, 50-day, 100-day, and 200-day lag lengths. However, to further test robustness through random switching strategy, only 10-day lag length is considered. The notion of random switching strategy can be explained as follows: a coin is tossed every day, and if by doing so the uniform distribution provides a probability greater than .5, the random strategy is to invest in the market; in risk-free security otherwise. This process is repeated 10 times for every stock. It means under random strategy; first stock has 10 returns against each day. Then daily returns on 30-day T-bill are subtracted from the respective returns of all days, and for all columns, to calculate excess returns produced by random switching strategy. Each column of excess returns thus calculated is regressed upon excess returns on the market to yield 10 regressions, average returns, alphas, and t-statistics. The averages of all these values are reported in last two columns of Table 3. The exact process is reiterated for other random strategy groups.

Finally, it is of interest to see how often daily signals help MA strategy to trade. Consider any stock. A trade happens only if, on a particular day, MA return is equal to buy-and-hold return; and, on the previous day, MA return is equal to risk-free return. Alternatively, a trade also occurs when the situation is reversed; that is if, on a particular day, MA return is equal to the risk-free return; and, on the previous day, MA return is equal to buy-and-hold return. After counting for a number oftrades, we can quickly calculate average hold period, a fraction of trading days and breakeven transaction cost (BETC).

As a final note, we would like to explain how we sorted all stocks into five quantiles. We construct five quantiles based upon the standard deviation (volatility) of each stock from a buy-and-hold strategy. Similarly, we create a differential quantile whose returns are equal to the difference between returns of stocks in the highest and the lowest quantiles. The stocks belonging to each quantile remain the same throughout the process. So, each reported figure is the average of all stocks into a quantile.

Results and Discussion

Performance of Buy-and-Hold and Moving Average (MA) Strategy

a. Descriptive Statistics

Table 1: Descriptive Statistics

Ranks	Panel A				Panel B				Panel C				
	Buy-and-Hold Strategy				MA Investment Timing Strategy				Performance of MA Investment Timing Strategy				
	Volatility Quantiles				MA(10) Timings Quantiles				MAGs				
	Average Return	Standard Deviation	Skewness	Sharpe Ratio	Average Return	Standard Deviation	Skewness	Sharpe Ratio	Average Return	Standard Deviation	Skewness	Sharpe Ratio	Success of MA Strategy
1(L)	11.54	22.14	0.55	0.34	11.03**	14.27	2.33	-25.81	-0.49	16.76	-0.16	-10.48	0.34
	(0.94)				(4.02)				(1.17)				
2	9.38	34.45	0.61	0.19	11.93	22.75	1.34	0.39	2.55	25.59	-0.37	-0.04	0.38
	(0.89)				(1.73)				(0.30)				
3	5.60	43.50	0.82	0.07	17.60*	28.27	2.68	0.52	12.05	32.63	-0.45	0.26	0.39
	(0.54)				(2.01)				(1.02)				
4	1.15	60.97	2.20	-0.03	19.25	37.69	4.56	0.42	18.16	47.15	-1.61	0.33	0.40
	(0.11)				(1.56)				(1.19)				
5(H)	1.99	99.70	6.05	-0.03	6.45	60.76	6.60	0.04	4.52	77.27	-6.73	0.08	0.40
	(0.06)				(0.34)				(0.29)				
H-L	-10.72	101.21	4.48	-0.35	-13.56	61.79	4.52	-0.32	-2.83	78.08	-4.91	0.07	0.02
	(-0.19)				(-0.34)				(0.07)				

Table 1 summarizes various aspects of returns (performance) on quantiles, MA (10 days) timing groups, and the respective MAGs. In Panel-A, we report several statistics of returns on five volatility quantile groups under buy-and-hold strategy namely average return, standard deviation, skewness, and Sharpe ratio. Table 1 also represents the performance of differential quantile, the difference between the highest and the lowest quantile, as its last row. The insignificance of average returns across all groups suggests we do not have substantial evidence supporting the performance of the buy-and-hold strategy in either way. Despite the fact, we comment on the results as follows. The rising volatility and decreasing average returns lead to a dipping Sharpe ratio across quantiles. More importantly, increasing skewness across most quantile groups indicates that the groups accompany a higher chance for significant positive returns.

Panel-B shows that only the returns of the first, 11.03% per annum, and the third group, 17.6% per annum, are significant. However, relaxing the level of significance a bit, the returns of second and fourth groups, with t-stats 1.73 and 1.56 respectively (reasonably close to 1.96), may also qualify for significance. Now the results of 10-days moving average timing strategy make sense in that the average returns on most MA groups are not only higher than that of buy-and-hold strategy but are an increasing function of quantiles, except the fifth and differential groups. However, for all quantiles, the standard deviations of MA groups are substantially lower than buy-and-hold groups. Consider a case of the lowest and the highest groups an example. The annualized standard deviation of the lowest and the highest groups under buy-and-hold strategy are 22.14% and 99.70% respectively; whereas the same groups produce the standard deviations as 14.27% and 60.76% in case of MA strategy. The findings also depict that the average returns of all groups have sizeable positive skewness which ranges between 1.34 and 6.60; though it also shows an increasing trend from the second to the highest group. However, first and differential groups are an exception here. It points out the fact that all MA group returns not only have the chance to produce substantial positive returns, but the volatility enhances this chance for most MA groups indeed. Since four MA quantiles, second, though the highest, enjoy increasing average returns with lower standard deviations, as directly opposed to buy-and-hold groups, they yield positive Sharpe ratios. Although inconsistent across quantiles, most of the findings in Panel-B appear to suggest that MA strategy performs slightly better than buy-and-hold strategy in timing individual stocks.

Panel-C shows the superior performance results of MAGs, the difference between MA returns and volatility quantile returns. The average returns across all quantiles are not significant. Therefore, the results provide no evidence supporting the superior performance of MA strategy over buy-and-hold strategy. Additionally, we comment on the remaining results of Panel-C as follow. As compared to volatility groups, MAG groups yield mixed findings regarding lower standard deviations, higher Sharpe ratios, and, most importantly, negative skewness across most of the quantiles. Negative skewness indicates the possibility of significant negative returns by MAGs. When comparing among volatility, MA, and MAG quantiles, we also note that the standard deviations of MAGs fall somewhere between the standard deviations of corresponding MA and volatility quantiles, lower than that of volatility quantiles but higher than MA quantiles. Finally, the success ratios across most

MAGs, ranging from 34% to 40%, point towards failure instead. Hence, Panel-C does not provide sufficient evidence in support of MA strategy outperforming the buy-and-hold strategy.

To conclude the discussion on results presented in Table 1, it is evident that based upon average returns of groups, we fail to conclude that MA timing strategy outperforms the buy-and-hold strategy when applied to individual stocks-despite of the fact that MA strategy yields some higher returns and low standard deviations. Instead, the results of skewness, Sharpe ratio, and success ratio indicate otherwise. However, the results are too inconsistent to draw any conclusion whatsoever. We further attempt to explain MAGs by using a risk-based model that is Capital Asset Pricing Model (CAPM)

b. Explanation of MAGs Using CAPM Regression

Table 2: CAPM Results

Rank	A	βMKT	Adj.R^2 (%)
1(L)	2.38	-0.15**	5.05
	(1.18)	(-8.53)	
2	3.38	-0.26**	5.71
	(0.32)	(-11.32)	
3	12.18	-0.27**	4.56
	(1.04)	(-9.10)	
4	18.39	-0.22**	1.64
	(1.22)	(-4.83)	
5(H)	4.93	-0.18**	0.43
	(0.30)	(-2.42)	
H-L	8.25	-0.21**	3.48
	(0.81)	(-7.24)	

Table 2 shows the results of CAPM regressions run between excess returns on groups (MAGs) and excess returns on the market under theMA-10 strategy. Adjusted r-squares are in percentages. Annualized alphas and betas also accompany t-stats in parenthesis. **, * denote the results are significant at 1% and 5% levels respectively. The sample period is from December 31, 1999, to February 29, 2016. See Data and Methodology Sectionfor calculations and other details.

Table 2 reports the results of regression for MAGs produced by 10-day moving average (MA-10) timing strategy. Note again that all risk-adjusted returns, the alphas, are insignificant. At one hand, the betas of all MAG quantiles are negative, highly significant, and range from -.15 to -.26 across quantiles; on the other hand, adjusted R^2 for most of the MAGs that varies from .43% to 5.71% across quantiles are extremely low. Low R^2 also confirms that stock returns, and ultimately MAGs, are highly volatile. Hence, coupling together results, beta and adjusted R^2, MAG returns do not move against the market. Moreover, excess market returns do not explain MAG returns well. Therefore, as the analysis does not offer evidence supporting the profitability of MA timing strategy, we can reasonably conclude that the results of Table 1 and Table 2 support each other.

Robustness Checks

Now, we test the robustness of these results in following two ways. First, we assess the performance (profitability) of MA strategy by using alternative lags, for instance, lag lengths with 20, 50, 100, 200 days. Then, we investigate the trading dynamics of MA strategy while accounting for transaction costs.

a. Alternative Lag Lengths

Table 3: MA Strategy Results

	MAG-20		MAG-50		MAG-100		MAG-200		Random Switching	
Rank	Average Return	A	Average Return	α	Average Return	α	Average Return	α	Average Return	A
1(L)	-0.93	1.81	-1.91	0.79	-2.73	-0.01	-2.75	-0.05	1.76	-0.60
	(1.03)	(1.03)	(0.73)	(0.72)	(0.55)	(0.55)	(0.45)	(0.45)	(0.02)	(-0.32)
2	1.54	2.35	0.27	0.98	-0.51	0.17	-0.07	0.66	5.77	6.52
	(0.18)	(0.19)	(0.00)	(0.01)	(-0.11)	(-0.11)	(-0.07)	(-0.06)	(0.03)	(1.04)
3	9.77	9.93	7.75	7.92	5.99	6.22	5.08	5.31	4.95	10.76
	(0.83)	(0.85)	(0.52)	(0.54)	(0.36)	(0.38)	(0.28)	(0.30)	(0.01)	(1.38)
4	15.62	15.86	12.29	12.54	9.26	9.53	7.79	8.06	-0.88	-7.50
	(1.00)	(1.03)	(0.75)	(0.78)	(0.55)	(0.58)	(0.44)	(0.46)	(0.00)	(-0.92)
5(H)	1.65	2.05	1.78	2.19	2.33	2.78	1.50	1.95	4.75	20.34
	(0.15)	(0.17)	(0.10)	(0.11)	(0.07)	(0.09)	(0.04)	(0.06)	(0.01)	(1.16)
H-L	-4.94	6.40	-3.83	4.88	0.91	3.73	2.22	3.18	3.58	1.92
	(-0.03)	(0.65)	(-0.02)	(0.43)	(0.02)	(0.30)	(0.02)	(0.24)	(0.03)	(0.53)

Table 3 presents the results of MA strategy when applied for alternative lag lengths namely 20-day, 50-day, 100-day, and 200-day. We also report the results of random strategy.All average returns and CAPM alphas are annualized with t-stats provided in parenthesis. **, * denote the results are significant at 1% and 5% levels respectively. The sample period is from December 31, 1999, to February 29, 2016. See Data and Methodology Section for calculations and other details.

Table 3 depicts the average returns and CAPM alphas of MAGs for alternative lag lengths. All alternative lag lengths bring similar findings as lag-10. Unfortunately, we find no average return and alphas as significant. For making a further comparison with MA strategy, last part of Table 3 reports the performance results, the average return, and alpha, generated by random switching strategy. The results indicate that the random switching strategy does not produce substantial results because all average returns and alphas are found extremely small and insignificant. Finally, after combining the results of MAG-10 with Table 3, the insignificance of all results provides no evidence to conclude that MA strategy performs better than buy-and-hold strategy when applied to individual stocks.

b. Trading Behavior

Table 4: Trading Behavior

Rank	MA-10				MA-20				MA-50				MA-100				MA-200			
	Holding Period	No. of Trades	Trading Fraction	BETC	Holding Period	No. of Trades	Trading Fraction	BETC	Holding Period	No. of Trades	Trading Fraction	BETC	Holding Period	No. of Trades	Trading Fraction	BETC	Holding Period	No. of Trades	Trading Fraction	BETC
1(L)	127.08	296	0.07	31.75	151.65	202	0.05	43.28	190.80	125	0.03	56.93	223.78	87	0.02	58.19	253.87	59	0.01	64.18
2	41.65	423	0.10	33.20	56.81	285	0.07	43.27	79.48	169	0.04	56.50	102.40	116	0.03	72.61	128.58	76	0.02	97.51
3	34.82	382	0.09	63.23	53.71	255	0.06	84.28	96.06	151	0.04	121.08	115.06	104	0.03	143.56	141.86	70	0.02	164.25
4	35.01	319	0.08	83.14	51.11	214	0.05	106.00	78.87	125	0.03	149.98	103.37	86	0.02	177.40	134.95	58	0.01	242.84
5(H)	31.09	281	0.07	36.59	46.28	196	0.05	42.52	66.49	119	0.03	56.81	94.16	80	0.02	102.74	124.90	56	0.01	158.65

Table 4 states the number of trades, fraction of trading days (trading fraction), average holding period, and BETCs (breakeven transaction costs measured in basis points) for each MA quantile across all lag lengths. The sample period is from December 31, 1999, to February 29, 2016. See Data and Methodology Section for calculations and other details.

Table 4 reports the results of the average holding period, no. of trades, a fraction of trading days, and breakeven transaction costs (BETC) of MA strategy for each quantile across all lag lengths. Note that BETC is the transaction cost which makes the MAG average return equal to zero. As discussed in Material and Method section, the fundamental notion of MA strategy is to use daily signals to make trades. Here the primary concern is the frequency of trading since it has to do with transaction costs. The more the strategy trades, the higher the transaction costs would be. Therefore, too many trades can make the survival of abnormal returns vulnerable to transaction costs. It necessitates seeing whether these abnormal returns can still hold after offsetting for transactions costs. As groups are formed based upon volatility, the performance of MA strategy should improve as we move towards groups with higher volatility. That is, for MA strategy to be successful, following results should hold:

from the lowest to the highest quantile, no. of trades and a fraction of trading should rise whereas average holding period, and BETC should fall. See how results in Table 4 meet these criteria.

Note that no. of trades, trading fraction, and BETC for the second to fourth quantile show opposite trend, except for the highest and the lowest quantiles. One can easily see that irrespective of the lag length, as volatility rises, no. of trades and fraction of trading days tend to decline while BETC rises. However, holding period tends to fall with rising volatility. Despite the fact, all BETCs are relatively large and well above the actual transaction costs in the UK (.45bp to 1.35pb)[1],the majority of our results go against the success of MA strategy. Therefore, most of the evidence presented inTable4 lead to the reverse conclusion, that is, across all lag lengths and most quantiles, MA strategy trades less with increasing transaction costs. Therefore, we can finally conclude that when MA investment timing strategy is applied to the individual stocks, most of the results provide no evidence of its superior performance as compared to buy-and-hold strategy. Instead results of trading behavior indicate towards the failure of MA strategy.

A Note on Insignificant Results quoted

In statistical analysis, as the holding period gets shortened, the likeliness of data showing random noise increases (Brigham & Ehrhardt, 2013), and this may be the reason why most of the results are insignificant. Remember t-stat is also known as signal-to-noise ratio. Here signal and noise are represented by average return and standard error respectively. Notably, Table1 depicts most of the average returns to be quite healthy but having more substantial standard deviations. It leads to more significant standard errors, which substantially lower the t-stats. So, it may be argued that the daily returns on which the whole analysis is based be quite noisy, making the most results insignificant. The comparison of performance results of individual stocks and portfolios is evident in the following section.

Portfolios versus Individual Stocks- Performance of MA Strategy

Now, we are in a position to compare the results of MA strategy for portfolios and individual stocks.

1 As quoted by Trading Services Price List (On-Exchange and OTC) published by London Stock Exchange, effective from February 1, 2016.

Table 5: Comparison of Table 1

	Panel A				Panel B				Panel C				
	Buy-and-Hold Strategy				MA(10) Timings Strategy				MAGs				
Ranks	Average Return	Standard Deviation	Skewness	Sharpe Ratio	Average Return	Standard Deviation	Skewness	Sharpe Ratio	Average Return	Standard Deviation	Skewness	Sharpe Ratio	The success of MA Strategy
1(L)	11.54	22.14	0.55	0.34	11.03**	14.27	2.33	-25.81	-0.49	16.76	-0.16	-10.48	0.34
	(0.94)				(4.02)				(1.17)				
2	9.38	34.45	0.61	0.19	11.93	22.75	1.34	0.39	2.55	25.59	-0.37	-0.04	0.38
	(0.89)				(1.73)				(0.30)				
3	5.60	43.50	0.82	0.07	17.60*	28.27	2.68	0.52	12.05	32.63	-0.45	0.26	0.39
	(0.54)				(2.01)				(1.02)				
4	1.15	60.97	2.20	-0.03	19.25	37.69	4.56	0.42	18.16	47.15	-1.61	0.33	0.40
	(0.11)				(1.56)				(1.19)				
5(H)	1.99	99.70	6.05	-0.03	6.45	60.76	6.60	0.04	4.52	77.27	-6.73	0.08	0.40
	(0.06)				(0.34)				(0.29)				
H-L	-10.72	101.21	4.48	-0.35	-13.56	61.79	4.52	-0.32	-2.83	78.08	-4.91	0.07	0.02
	(-0.19)				(-0.34)				(0.07)				
Portfolios	**Buy and Hold Strategy**				**MA(10) Timings Strategy**				**MAPs**				
1(L)	3.33**	4.89	-1.70	0.103	11.68**	2.86	-0.50	3.09	8.39**	3.90	2.91	1.42	0.61
	(2.66)				(15.91)				(8.37)				
2	5.04*	8.80	-1.21	0.25	15.35**	5.20	-0.59	2.4	10.34**	7.03	1.94	1.06	0.58
	(2.23)				(11.49)				(5.72)				
3	3.19	10.51	-1.11	0.034	17.75**	6.06	0.16	2.45	14.55**	8.50	1.99	1.37	0.58
	(1.18)				(11.39)				(6.67)				
4	-1.51	11.86	-1.04	-0.36	21.78**	6.91	0.52	2.74	23.22**	9.45	2.13	2.15	0.60
	(-0.49)				(12.28)				(9.56)				
5(H)	23.54**	15.06	-0.22	1.37	46.18**	10.49	1.57	4.12	22.49**	10.42	1.88	1.88	0.61
	(6.09)				(17.14)				(8.40)				
H-L	20.20**	12.83	0.51	1.35	34.50**	9.93	1.64	3.18	14.10**	8.60	0.60	1.31	0.30
	(6.14)				(13.53)				(6.37)				

See Table 5 for this comparison. It contains information of portfolios as well as individual stocks. It is evident that applying MA strategy to portfolios brings better results than to individual stocks-which accompany inconclusive evidence. Mostly, MA portfolios not just produce significantly positive and increasing returns, lower standard deviations, and higher Sharpe and success ratios relative to individual stocks-MA groups, but they also perform better than buy-and-hold portfolios. There could be two reasons for this superior performance- noise in daily returns and diversification effect. Impact of noise can easily be seen in the form of higher standard deviations and ultimately lower t-stats for all individual stock groups. Moreover, the better portfolio returns with lower standard deviations may also imply the benefits of diversification.

Table 6: Comparison of Table 2

Rank	Individual Stock Group MAGs			Portfolio MAPs		
	A	$_{\beta}$MKT	Adj.R^2(%)	α	$_{\beta}$MKT	Adj.R^2(%)
1(L)	2.38	-0.15**	5.05	8.47**	-0.11**	30.28
	(1.18)	(-8.53)		(10.13)	(-41.41)	
2	3.38	-0.26**	5.71	10.52**	-0.24**	43.18
	(0.32)	(-11.32)		(7.72)	(-54.77)	
3	12.18	-0.27**	4.56	14.77**	-0.30**	44.82
	(1.04)	(-9.10)		(9.11)	(-56.62)	
4	18.39	-0.22**	1.64	23.45**	-0.31**	39.07
	(1.22)	(-4.83)		(12.37)	(-50.31)	
5(H)	4.93	-0.18*	0.43	22.67**	-0.24**	19.62
	(0.30)	(-2.42)		(9.45)	(-31.05)	
H-L	8.25	-0.21**	3.48	14.19**	-0.13**	8.19
	(0.81)	(-7.24)		(6.69)	(-18.79)	

The Table 6 is highlighting some more features. When comparing with individual stocks, note all portfolio alphas are highly significant and increasing. Similarly, all betas accompany bigger t-stats and with substantially higher adjusted r squares.

Table 7: Comparison of Table 3

Groups	**MAG-20**		**MAG-50**		**MAG-100**		**MAG-200**		**Random Switching**	
Rank	**Average Return**	**A**	**Average Return**	α	**Average Return**	α	**Average return**	**A**	**Average Return**	A
1(L)	-0.93	1.81	-1.91	0.79	-2.73	-0.01	-2.75	-0.05	1.76	-0.60
	(1.03)	(1.03)	(0.73)	(0.72)	(0.55)	(0.55)	(0.45)	(0.45)	(0.02)	(-0.32)
2	1.54	2.35	0.27	0.98	-0.51	0.17	-0.07	0.66	5.77	6.52
	(0.18)	(0.19)	(0.00)	(0.01)	(-0.11)	(-0.11)	(-0.07)	(-0.06)	(0.03)	(1.04)
3	9.77	9.93	7.75	7.92	5.99	6.22	5.08	5.31	4.95	10.76
	(0.83)	(0.85)	(0.52)	(0.54)	(0.36)	(0.38)	(0.28)	(0.30)	(0.01)	(1.38)
4	15.62	15.86	12.29	12.54	9.26	9.53	7.79	8.06	-0.88	-7.50
	(1.00)	(1.03)	(0.75)	(0.78)	(0.55)	(0.58)	(0.44)	(0.46)	(0.00)	(-0.92)
5(H)	1.65	2.05	1.78	2.19	2.33	2.78	1.50	1.95	4.75	20.34

Table 7 (Continued)

	(0.15)	(0.17)	(0.10)	(0.11)	(0.07)	(0.09)	(0.04)	(0.06)	(0.01)	(1.16)
H-L	-4.94	6.40	-3.83	4.88	0.91	3.73	2.22	3.18	3.58	1.92
	(-0.03)	(0.65)	(-0.02)	(0.43)	(0.02)	(0.30)	(0.02)	(0.24)	(0.03)	(0.53)
Portfolios	**MAP-20**		**MAP-50**		**MAP-100**		**MAP-200**		**Random Switching**	
1(L)	8.41**	8.48**	7.37**	7.47**	6.64**	6.74**	4.59**	4.8**	2.58	0.65
	(8.36)	(10.12)	(7.37)	(9.06)	(6.94)	(8.48)	(5.40)	(6.61)	(0.04)	(0.84)
2	9.93**	10.08**	8.14**	8.36**	7.93**	8.19**	5.23**	5.74**	3.42	1.42
	(5.34)	(7.4)	(4.41)	(6.24)	(4.37)	(6.2)	(3.16)	(4.62)	(0.03)	(1.08)
3	13.02**	13.2**	11.67**	11.95**	10.45**	10.78**	6.17**	6.84**	2.54	0.51
	(5.88)	(8.22)	(5.12)	(7.39)	(4.60)	(6.69)	(2.88)	(4.34)	(0.02)	(0.33)
4	21.05**	21.24**	17.86**	18.16**	14.49**	14.84**	8.92**	9.69**	0.23	-1.79
	(8.51)	(11.17)	(7.01)	(9.53)	(5.62)	(7.72)	(3.54)	(5.11)	(0.00)	(-0.96)
5(H)	19.82**	19.97**	14.16**	14.37**	7.47**	7.71**	0.40	0.91	12.81	10.80**
	(7.38)	(8.3)	(5.10)	(5.78)	(2.70)	(3.11)	(0.15)	(0.38)	(0.07)	(4.21)
H-L	11.41**	11.48**	6.78**	6.89**	0.82	0.96	-4.19	-3.88	11.12	9.18**
	(5.11)	(5.37)	(2.92)	(3.1)	(0.35)	(0.42)	(-1.83)	(-1.77)	(0.06)	(4.03)

Table 7 also supports the better performance of MA strategy for portfolios as most of the average returns and alphas are significant across all portfolios, overall lag lengths, except random switching which do not provide robust results even in case of portfolios.

Table 8: Comparison of Table 4

	MA-10				MA-20				MA-50				MA-100				MA-200			
Rank	Avg. Holding Period	No. of Trades	Trading Fraction	BETC	Avg. Holding Period	No. of Trades	Trading Fraction	BETC	Avg. Holding Period	No. of Trades	Trading Fraction	BETC	Avg. Holding Period	No. of Trades	Trading Fraction	BETC	Avg. Holding Period	No. of Trades	Trading Fraction	BETC
1(L)	127.08	296	0.070	31.75	151.65	202	0.048	43.28	190.80	125	0.030	56.93	223.78	87	0.021	58.19	253.87	59	0.015	64.18
2	41.65	423	0.100	33.20	56.81	285	0.068	43.27	79.48	169	0.041	56.50	102.40	116	0.028	72.61	128.58	76	0.018	97.51
3	34.82	382	0.091	63.23	53.71	255	0.060	84.28	96.06	151	0.036	121.08	115.06	104	0.025	143.56	141.86	70	0.018	164.25

Table 8 (Continued)

4	35.01	319	0.076	83.14	51.11	214	0.051	106.00	78.87	125	0.030	149.98	103.37	86	0.021	177.40	134.95	58	0.014	242.84
5(H)	31.09	281	0.067	36.59	46.28	196	0.046	42.52	66.49	119	0.029	56.81	94.16	80	0.019	102.74	124.90	56	0.014	158.65
	MA-10				MA-20				MA-50				MA-100				MA-200			
1(L)	9.64	408	0.100	31.22	15.93	246	0.062	51.80	29.14	133	0.034	83.36	60.25	63	0.016	156.39	70.86	52	0.013	127.75
2	8.71	452	0.110	34.74	14.41	272	0.069	55.32	22.19	175	0.044	69.93	52.10	73	0.018	161.32	76.65	48	0.012	157.72
3	8.96	439	0.110	50.33	13.81	284	0.072	69.42	25.52	152	0.038	115.40	56.70	67	0.017	231.55	70.86	52	0.013	171.62
4	9.81	401	0.100	87.92	15.80	248	0.062	128.56	31.24	124	0.031	216.51	45.36	84	0.021	255.97	61.57	60	0.015	215.02
5(H)	10.17	387	0.098	88.23	16.46	238	0.060	126.00	35.50	109	0.027	195.22	44.83	85	0.022	130.39	72.23	51	0.013	11.41

Table 8 which showsthe trading behavior of both strategies brings almost similar results. In both cases, we observe opposite trends across quantile and groups. Instead of increasing, no. of trades and trading fraction tend to fall. On the other hand, BETC rises across portfolios and groups instead of falling, however, remains well above the actual transaction cost in the UK.

Conclusion

First, we apply MA investment timing strategy to the groups of individual stocks sorted by volatility. The fact that overwhelming majority of results under MA or buy-and-hold strategies are insignificant helps to maintain that there is no evidence to support the superiority of either strategy when applied to individual stocks. However, trading behavior and success ratios across groups provide some mixed results while indicating more towards the failure of MA strategy. We argue that prevalent noise in daily stock return data is the reason for such consistency in insignificant results.

Second, when applied to volatility-sorted portfolios, MA strategy substantially beats the buy-and-hold strategy by yielding higher average return and risk-adjusted return, lower standard deviation, large-and-positive skewness and Sharpe ratio, and considerable success ratios across portfolios. Both for individual stocks and portfolios, returns and especially trading behavior suggest that the performance of MA strategy diminishes as we go farther in history; that is, the longer the lag length, the worse the performance.

References

Allen, F., & Karjalainen, R. (1999). Using genetic algorithms to find technical trading rules1. *Journal of financial economics, 51*(2), 245-271.

Brigham, E. F., & Ehrhardt, M. C. (2013). *Financial management: Theory & practice*: Cengage Learning.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of finance, 47*(5), 1731-1764.

Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis, 48*(5), 1433-1461.

Han, Y., Zhou, G., & Zhu, Y. (2016). A trend factor: Any economic gains from using information over investment horizons? *Journal of financial economics, 122*(2), 352-375.

Hoffmann, A. O., & Shefrin, H. (2014). Technical analysis and individual investors. *Journal of Economic Behavior & Organization, 107*, 487-511.

Hudson, R., Dempsey, M., & Keasey, K. (1996). A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices-1935 to 1994. *Journal of Banking & Finance, 20*(6), 1121-1132.

Kwon, K.-Y., & Kish, R. J. (2002). Technical trading strategies and return predictability: NYSE. *Applied Financial Economics, 12*(9), 639-653.

Lukac, L. P., & Brorsen, B. W. (1990). A comprehensive test of futures market disequilibrium. *Financial Review, 25*(4), 593-622.

Metghalchi, M., Marcucci, J., & Chang, Y.-H. (2012). Are moving average trading rules profitable? Evidence from the European stock markets. *Applied Economics, 44*(12), 1539-1559.

Mills, T. C. (1997). Technical analysis and the London Stock Exchange: Testing trading rules using the FT30. *International Journal of Finance & Economics, 2*(4), 319-331.

Neely, C. J. (1997). Technical analysis in the foreign exchange market: a layman's guide. *Federal Reserve Bank of St. Louis Review*(Sep), 23-38.

Roberts, M. C. (2005). Technical analysis and genetic programming: constructing and testing a commodity portfolio. *Journal of Futures Markets, 25*(7), 643-660.

Shintani, M., Yabu, T., & Nagakura, D. (2012). Spurious regressions in technical trading. *Journal of Econometrics, 169*(2), 301-309.

Sullivan, R., Timmermann, A., & White, H. (1999). Data-snooping, technical trading rule performance, and the bootstrap. *The Journal of finance, 54*(5), 1647-1691.

Taylor, M. P., & Allen, H. (1992). The use of technical analysis in the foreign exchange market. *Journal of international Money and Finance, 11*(3), 304-314.

Wei, L.-Y., Cheng, C.-H., & Wu, H.-H. (2014). A hybrid ANFIS based on n-period moving average model to forecast TAIEX stock. *Applied Soft Computing, 19*, 86-92.

Zhou, G., & Zhu, Y. (2013). An equilibrium model of moving-average predictability and time-series momentum. *Unpublished working paper, Washington University in St. Louis*.