Market Timing with Moving Averages[1]

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April 15, 2015

[1]I would like to thank Syed Zamin Ali, Tze Chuan 'Chewie' Ang, B. Ross Barmish, Jean Canil, Don Chance, Sudipto Dasgupta, Daisy Doan, Victor Fang, Berowne Hlavaty, Daniel Orlovsky, James Primbs, Bruce Rosser, Vincent Xiang, Takeshi Yamada, Alfred Yawson, Xinwei Zheng, Edward Zychowicz as well as seminar participants at Deakin University and the University of Adelaide and participants in the 2012 Australasian Finance and Banking conference in Sydney, the 2014 J.P.Morgan quantitative conference in Sydney and the 2013 Midwest Finance Association meetings in Chicago. In addition, I would like to express my gratitude to the editor, Huining Cao, and two anonymous referees for their very detailed and thoughtful comments. Any remaining errors are my own responsibility.

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Abstract

I present evidence that a moving average (MA) trading strategy has a greater average return and skewness as well as a lower variance compared to buying and holding the underlying asset using monthly returns of value-weighted US decile portfolios sorted by market size, book-to-market, and momentum, seven international markets as well as 18,000 individual US stocks. The MA strategy generates risk-adjusted returns of 3% to 7% per year after transaction costs. The performance of the MA strategy is driven largely by the volatility of stock returns and resembles the payoffs of an at-the-money protective put on the underlying buy-and-hold return. Conditional factor models with macroeconomic variables, especially the default premium, can explain some of the abnormal returns. Standard market timing tests reveal ample evidence regarding the timing ability of the MA strategy.

Key Words: Market timing, security selection, moving average, technical analysis, conditional models.

JEL Classification: G11, G12, G14.

1 Introduction

Technical analysis involves the use of past and current market price, trading volume and, potentially, other publicly available information to predict future market prices. It is highly popular in practice with plentiful financial trading advice that is based largely, if not exclusively, on technical indicators. In a perhaps belated testament to this fact consider the following quote from the *New York Times*'s issue dated March 11, 1988: *"Starting today the New York Times will publish a comprehensive three-column market chart every Saturday... History has shown that when the S&P index rises decisively above its (moving) average the market is likely to continue on an upward trend. When it is below the average that is a bearish signal."* According to Brock, Lakonishok and LeBaron (1992), the moving average in its various implementations, is the most popular strategy followed by investors who use technical analysis. More formally, Brock, Lakonishok and LeBaron (1992) find evidence that some technical indicators do have a significant predictive ability. Blume, Easley and O'Hara (1994) present a theoretical framework using trading volume and price data leading to technical analysis being a part of a trader's learning process. A more thorough study of a large set of technical indicators by Lo, Mamaysky and Wang (2000) also found some predictive ability especially when moving averages are concerned. Zhu and Zhou (2009) provide a solid theoretical reason why technical indicators could be a potentially useful state variable in an environment where investors need to learn over time the fundamental value of the risky asset they invest in. More recently, Neely, Rapach, Tu and Zhou (2010,2011) find that technical analysis has as much forecasting power over the equity risk premium as the information provided by economic fundamentals. The practitioners literature also includes Faber (2007) and Kilgallen (2012) who thoroughly document the risk-adjusted returns to the moving average strategy using various portfolios, commodities and currencies. In addition, Huang and Zhou (2013) use the moving average indicator to predict the return on the US stock market while Goh et al. (2013) apply the same idea to government bond yields and risk premia. Motivated in part by the predictive power of the moving average indicator, Han and Zhou (2013) and Jiang (2013) construct a trend factor with considerable cross-sectional explanatory power and substantial historical performance.

The main findings of this study are as follows. First, I present evidence that the returns to a simple moving average switching strategy dominate in a mean-variance sense the returns to a buy-and-hold strategy of the underlying portfolio. Second, I demonstrate that the switching strategy involves infrequent trading with relatively long periods when the moving average strategy is invested in the underlying assets and the break-even transaction costs are on the order of 3% to 7% per transaction. Thirdly, even though there is overwhelming evidence of imperfect market timing ability of the moving average switching strategy for a single portfolio or individual stocks, cross-sectional differences remain between the abnormal returns of different portfolios. These differences persist when controlling for the four-factor Carhart (1997) model for portfolios formed on past price returns and are mostly driven by differences in the volatility of portfolio and stock returns. Fourthly, conditional models explain to a certain degree the moving average abnormal returns but do not completely eliminate them. Fifth, I document the performance of the moving average strategy using more than 18,000 individual stocks from the Center for Research in Security Prices. Sixth, I present evidence of the robustness of the performance of the moving average strategy in seven international stock markets. Seventh, I show that the lagged indicator regarding the switch into or out of the risky asset has substantial predictive ability over subsequent portfolio returns over and above the predictability contained in standard instrumental variables, like the default spread, investor sentiment, recession dummy variable and liquidity risk. Last but not least, the strategy is robust to randomly generated stock returns and bootstrapped historical returns. Nevertheless, a random switching strategy leads to negative and statistically significant returns. The inferior performance of random switching is a testament to the market timing ability of the moving average strategy. Furthermore, random switching generates increasingly poorer average returns as we investigate its performance with riskier underlying assets. This is also consistent with the performance being driven by volatility.

This paper is similar in spirit to Han, Yang and Zhou (2013). However, several important differences stand out. First, I use monthly value-weighted returns of decile portfolios constructed by various characteristics like size, book-to-market, and momentum.[1] Value-weighted portfolios at a monthly frequency should have a much smaller amount of trading going on inside the portfolio compared to the daily equal-weighted portfolios investigated by Han, Yang and Zhou (2013). Secondly, the cross-sectional results in this study are just an artefact of the decile portfolios and not the main focus of this paper while Han, Yang and Zhou (2013) is mostly concerned with the inability of standard empirical tests to account for the moving average strategy average returns differences across portfolios. I argue that this is largely due to using the wrong benchmark pricing model. Using a dynamic market-timing tests and conditional asset pricing models with

[1] Further findings using cash-flow-to-price, earnings-to-price, dividend-price, past return, and industry are broadly consistent with those reported in the text and are available from the author upon request.

macroeconomic state variables leads to mostly negative or statistically insignificant risk-adjusted returns for the moving average strategy. In light of this, my take on the performance of the moving average strategy is that it is not an anomaly but instead a dynamic trading strategy that exposes investors to potential upside returns derived from risky assets via its market timing ability. This performance is more pronounced the more volatile the returns of the underlying risky assets are. A final caveat I need to make is that the performance of the strategy is investigated using historical returns rather than actually trading in financial markets. It is likely that in reality there may be adverse price impact of liquidating and initiating large positions, especially for less liquid assets with lower trading volumes. This possibility is in the spirit of limits to arbitrage as another potential explanation for the performance of the moving average strategy. The nature of this empirical study is such that this potential explanation cannot be eliminated.

The highlights of this study are the superior performance of the moving average portfolios relative to buying and holding the underlying portfolios, the infrequency of trading and the very large break-even transaction costs, the fact that the switching strategy returns resemble an imperfect at-the-money protective put, and that cross-sectional differences are not a new anomaly as maintained in Han, Yang and Zhou (2013) but are due to volatility differences in the underlying portfolios and stocks. An asset with 10% higher standard deviation of returns will experience on average between 2% and 3.5% mean return improvement between the buy-and-hold and the moving average strategy. The returns of the moving average strategy relative to the buy-and-hold strategy exhibit a lot of convexity and, hence, will be hard to explain using standard linear asset pricing models. The anomalous risk-adjusted performance relative to standard models appears to be largely due to omitting market timing factors in a simple piece-wise linear framework that captures the moving average strategy's convexity. Furthermore, the moving average strategy appears to be antifragile in the sense of Taleb (2012) meaning that for securities with more volatile returns there is a greater improvement of the moving average returns relative to buy-and-hold returns.

2 Moving Average Market Timing Strategies

I use monthly value-weighted[2] returns of sets of ten portfolios sorted by market value, book-to-market, and momentum. The data is readily available from Ken French Data Library. The sample period starts in January 1960 and ends in December 2011.

The following exposition of the moving average strategy follows closely the presentation in Han, Yang, and Zhou (2013). Let R_{jt} be the return on portfolio j at the end of month t and let P_{jt} be the respective price level of that portfolio. Define the moving average of portfolio j $A_{jt,L}$ at time t with length L periods as follows:

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

Throughout most of the paper, I use a moving average of length $L = 24$ months as baseline case. Later on, in the section dealing with robustness checks I also present results for all sets of portfolios with lags of 6-months, 12-months, 36-months, 48-months, and 60-months. The way I implement the moving average strategy in this paper is to compare the closing price P_{jt} at the end of every month to the running moving average $A_{jt,L}$. If the price is above the moving average this triggers a signal to invest (or stay invested if already invested at $t-1$) in the portfolio in the next month $t+1$. If the price is below the moving average this triggers a signal to leave the risky portfolio (or stay invested in cash if not invested at $t-1$) in the following month $t+1$.[3] As a proxy for the risk-free rate, I use the return on the 30-day US Treasury Bill.

More formally, the returns of the moving average switching strategy can be expressed as follows:

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

in the absence of any transaction costs imposed on the switches. For the rest of the paper and in all of the empirical results quoted I consider returns after the imposition of a one-way transaction cost of τ.

[2] I use value-weighted portfolio returns to control for the amount of rebalancing trading inside the various portfolios. The empirical results in this paper are much stronger when equal-weighted portfolios are used. However, this may understate the break-even transaction costs as equal weighted portfolios require a lot of trading to be replicated. I also use monthly returns to limit the amount and frequency of trading of the various portfolios. The empirical results using daily portfolio returns are similar in spirit and generate higher abnormal returns without a disproportionate amount of additional trading.

[3] An alternative version of the switching strategy involves investing in the market portfolio instead of the risk-free asset. This version of the switching strategy has a somewhat inferior performance compared to the baseline case investigated in the article. Nevertheless, it is an interesting case to consider and I am grateful to an anonymous referee for suggesting this idea to me.

Mathematically, this leads to the following four cases in the post-transaction cost returns:

$$\tilde{R}_{jt,L} = \begin{cases} R_{jt}, & \text{if } P_{jt-1} > A_{jt-1,L} \text{ and } P_{jt-2} > A_{jt-2,L}, \\ R_{jt} - \tau, & \text{if } P_{jt-1} > A_{jt-1,L} \text{ and } P_{jt-2} < A_{jt-2,L}, \\ r_{ft}, & \text{if } P_{jt-1} < A_{jt-1,L} \text{ and } P_{jt-2} < A_{jt-2,L}, \\ r_{ft} - \tau, & \text{if } P_{jt-1} < A_{jt-1,L} \text{ and } P_{jt-2} > A_{jt-2,L}. \end{cases} \tag{3}$$

depending on whether the investor switches or not. Note that this imposes a cost on selling and buying the risky portfolio but no cost is imposed on buying and selling the Treasury bill. This is consistent with prior studies like Balduzzi and Lynch (1999), Lynch and Balduzzi (2000), and Han (2006), among others. Regarding the appropriate size of the transaction cost, Balduzi and Lynch (1999) propose using a value between 1 and 50 basis points. Lynch and Balduzi (2000) use a mid-point value of 25 basis point. In order to err on the side of caution, I use a value of 50 basis points in all the empirical results presented in the next section or $\tau = 0.005$.

I construct excess returns as zero-cost portfolios that are long the MA switching strategy and short the underlying portfolio to determine the relative performance of the moving average strategy against the buy-and-hold strategy. Denote the resulting difference between the return of the MA strategy for portfolio j at at the end of month t, $\tilde{R}_{jt,L} - R_{jt}$, and the return of portfolio j at the end of month t, R_{jt}, as follows:

$$\text{MAP}_{jt,L} = \tilde{R}_{jt,L} - R_{jt}, \quad j = 1, \ldots, N. \tag{4}$$

The presence of significant abnormal returns can be interpreted as evidence in favor of superiority of the moving average switching strategy over the buy-and-hold strategy of the underlying portfolio. Naturally, the moving average switching strategy is a dynamic trading strategy so it is perhaps unfair to compare its returns to the buy-and-hold returns of being long the underlying portfolio. Nevertheless, I impose conservatively large transaction costs and later report much larger break-even transaction costs.

3 Profitability of Moving Average Portfolios

In this section, I present summary statistics for the underlying portfolios performance, the performance of the moving average switching strategy, and the excess MAP returns for nine sets of ten portfolios sorted by market value, book-to-market ratios, and momentum. Next, I present the four-factor Carhart (1997) regression results for the MAP returns of each set of portfolios. Finally, I discuss the result in light of the potential reasons for the profitability of the moving average switching strategy.

3.1 Performance

Table 1 reports the first three moments and the Sharpe ratios of the underlying portfolios, the moving average (MA) switching strategy applied to each portfolio, and the excess return (MAP) of the MA switching strategy over the buying and holding (BH) of the underlying portfolio. The results are intriguing. First, the average annualized returns of the MA strategy are substantially higher than the average annualized returns of the underlying portfolios. Second, this average return difference come with a lower return standard deviation and, hence, the MA switching strategy appears to dominate the underlying BH portfolio strategy in a mean-variance sense[4]. Third, for the vast majority of portfolios, the underlying BH has a negative return skewness while the MA strategy in most cases exhibits positive skewness. This feature will make the MA switching strategy very attractive to investors who have a preference for skewness. Fourth, the risk-return trade-off is improved substantially resulting in much higher Sharpe ratios of the MA returns when compared to the Sharpe ratios of the BH returns. Fifth, these results hold for almost all portfolio across all sorting variables. Furthermore, there appear to be some substantial cross-sectional differences related to the size effect (Panel A), the value premium (Panel B) as well as momentum premia (Panels C).

Insert Table 1 here.

From the evidence presented in Table 1 it appears that portfolios with higher standard deviations tend to experience higher average improvements between the buy-and-hold and the moving average strategy performance or $\Delta\mu$. A more formal way to test this is through a cross-sectional regression which is presented

[4]Issues related to the statistical significance of the mean return improvement and the return standard deviation reduction are explored in the next section.

next:

$$\Delta\mu \quad = \quad -2.19 + 0.35\sigma, \tag{5}$$
$$\quad\quad\quad\quad (1.08) \quad (0.06)$$

where the cross-sectional $R^2 = 0.5834$ and the standard errors are corrected for heteroscedasticity and reported in parentheses. The slope on σ is highly statistically and economically significant suggesting that on average $\Delta\mu$ increases by 3.5% on an annualized basis when the portfolio return volatility increases by 10%.[5]

The MA strategy clearly performs very well compared to the BH strategy. The next section investigates more formally the reasons for this performance in the traditional empirical asset pricing framework of factor models and abnormal returns.

3.2 Abnormal Returns

The asset pricing model I consider in this section is the four-factor Carhart (1997) model:[6]

$$\mathrm{MAP}_{jt,L} = \alpha_j + \beta_{j,m} r_{mkt,t} + \beta_{j,s} r_{smb,t} + \beta_{j,h} r_{hml,t} + \beta_{j,u} r_{umd,t} + \epsilon_{jt}, \quad j = 1, \ldots, N, \tag{6}$$

where $r_{mkt,t}$ is the excess return on the market portfolio at the end of month t, $r_{smb,t}$ is the return on the SMB factor at the end of month t, $r_{hml,t}$ is the return on the HML factor at the end of month t, and $r_{umd,t}$ is the return of the UMD factor at the end of month t. Note that all of the risk-adjusted alphas are highly statistically statistically significant. Moreover, they are all still quite substantial economically ranging between 3% and 7% per year. The factor loadings on the market portfolio, SMB, and HML are largely unchanged across the three sets of decile portfolios while the loadings on the UMD factor are mostly positive and highly statistically significant (with the exception of momentum deciles 9 and 10). This suggests that all four factors have a role to play in driving the performance of the MAP returns. Nevertheless, the average adjusted R^2 values indicate that only around half of the return variation can be explained and

[5] A quick glance at Table 1 reveals that the Low momentum (extreme loser) portfolio has the highest σ as well as the highest $\Delta\mu$ suggesting that it might be an outlier. Dropping this observation from the cross-sectional regression reduces the magnitude of the slope coefficient to 0.16 but it is still statistically and economically significant.

[6] Results for the CAPM and Fama-French three factor models yield very similar and, frequently, stronger than the results for the Carhart (1997) model. These additional findings are not reported in the paper in the interest of saving space. They are available from the author upon request.

accounted for by the market portfolio return, size, value and momentum. This leaves a large portion of return variation that cannot be accounted for.

Insert Table 2 here.

3.3 Explanation

Before making an attempt at explaining the reasons for the profitability of the MA strategies performance, it is useful to inspect a scatter plot of the MA strategy returns versus the underlying BH strategy returns for the same portfolio. For ease of exposition I provide a plot for a single portfolio only.[7] Figure 1 presents the scatter plot for the first decile of the market-capitalization sorted deciles.

Insert Figure 1 about here.

The strategy is clearly triggering false positive signals where we are told to stay invested or switch into the underlying asset with a subsequent negative return (negative quadrant of returns in the figure). Similarly, there are a few instances of a false negative signal where we switch into the risk-free asset while the underlying risky asset has a positive excess return in the following period. Nevertheless, the signal is right about two out of every three times and in those instances the scatter plot resembles the payoff of an at-the-money put option combined with a long position in the underlying risky asset. This positive convexity is the driving factor for the relative outperformance of the moving average strategy relative to the buy-and-hold strategy. Holding the signal success rate constant, risky assets with more volatile returns will experience a higher average outperformance and this is evidenced in all of the previous tables.

3.4 Individual Stocks

In this subsection I report results on the performance of moving average strategies with individual stocks in the CRSP database starting in January 1960 until December 2011. This results in 28,685 individual stocks. I retain only the stocks for which a contiguous block of non-missing 48 monthly returns is available.[8] This leaves a total of 18,397 stocks. Instead of reporting the results in tabular form, I report the key attributes in Figure 2 as histograms.

[7]The scatter plots for the other portfolios sorted on the various characteristics are available from the author upon request.

[8]As a robustness check, I also consider requiring a longer series on non-missing monthly returns of 72 months and 84 returns. This results in a smaller number of stocks but does not materially change the results presented for the larger set of stocks with only 48 consecutive non-missing monthly returns. The additional results are available from the author upon request.

Insert Figure 2 about here.

The performance of the MA strategy with individual stocks is largely consistent with the performance of the MA strategy with portfolios. The risk of the MA strategy is uniformly always smaller than the risk of the underlying stock. The difference in average returns between the MA and BH strategies is positive for 18,078 or more than 98% of all individual stocks I investigate. The superior performance of the MA strategy over the BH strategy does not come at the cost of a large number of trades. The MA strategies of almost 10,000 stocks have between 1 and 10 switches during the sample period under consideration. The break-even transaction costs of 15,000 stocks are between 0 and 100 basis points. Bear in mind that the break-even transaction costs are in addition to the 50 basis point one-way transaction cost imposed in calculating the MA returns. Finally and, most importantly, for the vast majority of individual stocks, the probability of being on the right side of the market, p_1, is well above 50% with an average value of 72.4%.

Finally, I repeat the cross-sectional regression of $\Delta\mu$ on σ for all the individual stocks in the sample:

$$\begin{aligned} \Delta\mu &= \underset{(0.28)}{5.09} + \underset{(0.03)}{0.20}\sigma, \end{aligned} \tag{7}$$

where the cross-sectional $R^2 = 0.1198$ and the standard errors are corrected for heteroscedasticity and reported in parentheses. The slope on σ is highly statistically and economically significant suggesting that when σ increases by 10% the mean return of the moving average strategy is 2% higher than the mean return of the buy-and-hold strategy on an annualized basis. Despite the substantial cross-sectional variation in $\Delta\mu$ and σ at the level of individual stocks, the evidence still points towards volatility of the underlying security as the variable associated with the improvement in the mean return of the spread between MA and BH.

4 Robustness Checks

In this section, I report my findings for several robustness checks performed on the performance of the MA strategy versus the BH strategy for decile portfolios sorted on market capitalization, book-to-market ratios and momentum. First, I show evidence of the MA strategy performance in two subperiods of equal length. Second, I show how the MA strategy performs when various lag length are used. Third, I report the intensity of trading, the break-even transaction costs, the probability of being on the right side of the market, and the statistical significance of the mean return and standard deviation improvement. Finally, I also report how the number of trades and the break-even transaction costs vary with alternative lengths of the moving average.[9]

4.1 Subperiods

In this robustness check, I split the sample in two when the first half-period starts in January 1960 and ends in December 1986 while the second half-period starts in January 1987 and ends in December 2011. Overall, the results reported in previous section are robust with respect to the two sub-periods. The abnormal returns are a little smaller for size and momentum deciles but most are statistically significant in both subperiods.

4.2 Alternative Lag Lengths

Next, I investigate the effect of varying lengths of the moving average window on the magnitude of the average MAP returns for all the sets of portfolios under investigation. Specifically, I investigate the average MAP returns for moving average windows of 6 months, 12 months, 36 months, 48 months, and 60 months in length. The average returns are economically and statistically significant with moving average window lengths of less than 24 months, the baseline window used previously. The significant positive excess returns persist with moving average window length of 36 months and decrease markedly when I use longer window lengths of 48 and 60 months. Importantly, significant cross-sectional variation persists for all sets of portfolios with the exception of book-to-market portfolios. The range of annual MAP returns with a moving average window of 6 months is between roughly 8% and 21%. The range of annual MAP returns with the length of the moving average is 12 months is between approximately 5% and 15%. When I increase the moving average window length to 36 months the range of average annualized MAP returns drops to between 1% and 9%, depending on which sets of deciles I consider.

[9] The robustness checks presented here are only a small portion of the total number of robustness checks performed in preparing this article. Results for equal-weighted portfolio, both daily and monthly returns, double-sorted portfolio sets along size/book-to-market, volatility and size/past performance show the profitability of the MA switching strategy is robust with respect the frequency of the data, the portfolio construction and the portfolio composition. These additional results are available from the author upon request.

4.3 Statistical Significance, Trading Intensity and Break-Even Transaction Costs

Table 3 reports the statistical significance in the improvement of the average return $\Delta\mu$ of the MA portfolio over the BH portfolio as well as the reduction in the return standard deviation $\Delta\sigma$. The evidence points towards a substantial improvement in a mean-variance sense for all sets of portfolios under consideration. The annualized improvement in the average return ranges from 2% to 10% while the reduction in the standard deviation is between approximately 3% to 11%. The MA strategy is active more often than not ranging between 58% to 86% of the sample. Yet, the number of transactions, NT, is never above 60 and can be as little as 29 for decile 10 of the book-to-market sorted portfolios. In a sample of 600 months this translates into average holding periods of between 10 and 20 months where the MA strategy is continuously invested either in the risky asset or the risk-free asset. Next, I report the break-even transaction costs, BETC, calculated as the level of one-way proportional transaction cost in percent that would eliminate completely the average MAP portfolio return. The values of the BETC for the various sets of portfolio range between almost 3% to as high as 7%. This is a very large level of transaction costs which should more than compensate for the rebalancing costs associated with implementing the value-weighted portfolio scheme used to construct the portfolio returns. Finally, the last two columns report the fraction of months that the MA strategy generates a positive return (p_1) as well as a return that is in excess of the risk-free rate (p_2). I report the statistical significance of the null hypothesis that the true fraction of times is above 50%. With the exception of three momentum, all the observed fractions are highly statistically significant and range from 55% to 63% success rate of the MA strategy being on the right side of the market. These are considerably favorable odds and in line with the evidence reported previously about the superior performance of the MA switching strategy.

Insert Table 3 here.

The next robustness check I perform is to investigate the intensity of trading and its impact on break-even transaction costs at various lengths for the moving average window. As expected, the findings are that shorter window lengths lead to more intensive trading and vice versa. Similarly, the break-even transaction cost, BETC, decrease when shorter windows are used and increase or stay roughly the same when I increase the length of the moving average window.

The large values of BETC and the relatively small number of transactions NT suggest that the MA switching strategy is successful at improving the average returns compared to a buy-and-hold investment strategy. The superior performance is robust with respect to two subperiods, various lag lengths of the moving average window and persists for between 6 and 60 months with very reasonable intensity of trading and substantial break-even transaction costs. This suggests that the MA switching strategy will be of use to not only large institutional investors but will also be of value to individual investors. These findings are perhaps indicative of the reasons for the wide popularity of the moving average as a technical indicator in practice.[10]

5 Drivers of Abnormal Returns

In this section, I investigate the reasons for the superior returns of the MAP portfolios. To this end, I control the MAP performance for economic expansions and contractions as well as other state contingencies like the sign of the lagged market return. Furthermore, I investigate the conditional performance of the MAP returns while controlling for two instrumental variables with documented predictive power over stock returns and an additional risk factor to control of the possible presence of liquidity risks. Finally, I perform two simulations using bootstrapped returns and randomly generated returns.

5.1 Market Timing

The first approach towards testing for market timing ability is the quadratic regression of Treynor and Mazuy (1966):

$$\mathrm{MAP}_{jt,L} = \alpha_j + \beta_{j,m} r_{mkt,t} + \beta_{j,m^2} r_{mkt,t}^2 + \epsilon_{jt}, \quad j = 1, \ldots, N, \tag{8}$$

where statistically significant evidence of a positive β_{j,m^2} can be interpreted as evidence in favor of market timing ability. The second approach is to allow for a state-contingent $\beta_{j,m}$ based on the direction of move of the market return as in Henriksson and Merton (1981):

$$\mathrm{MAP}_{jt,L} = \alpha_j + \beta_{j,m} r_{mkt,t} + \gamma_{j,m} r_{mkt,t} I_{\{r_{mkt,t}>0\}} + \epsilon_{jt}, \quad j = 1, \ldots, N, \tag{9}$$

[10] Additional results are available from the author upon request.

where $I_{\{r_{mkt,t}>0\}}$ is an indicator function of the event of a positive market return. A statistically significant value of $\gamma_{j,m}$ is usually interpreted as evidence of successful market timing ability.

Table 4 presents the results of the two market timing regressions for various sets of value-weighted decile portfolios. Panel TM presents the empirical results from the Treynor and Mazuy (1966) quadratic regression while Panel HM presents the results for the state-contingent beta regression of Henriksson and Merton (1981). In both regressions, both β_{j,m^2} and $\gamma_{j,m}$ are highly statistically significant, indicating there is strong evidence of market timing ability of the switching moving average strategy. Nevertheless, the alphas of quite a few decile portfolios are also statistically significant at conventional levels. This suggests that market timing alone is not the sole driver of the abnormal returns generated by the switching moving average strategy.

Insert Table 4 here.

5.2 Business Cycles and Market States

Following Han, Yang and Zhou (2013), I investigate the performance of the MAP portfolio returns in economic expansions and contractions as well as in up and down markets as defined by the sign of the market return. Table 5 presents the results for the various sets of portfolio deciles. The evidence overwhelmingly indicates that MAP abnormal returns are higher during economic contractions and following positive market factor returns. For portfolios constructed by sorting on past performance (short-term/long-term reversal and medium-term momentum) there is also evidence of a significant cross-sectional differences between the High and Low MAP abnormal returns which cannot be accounted for by the four Carhart (1997) factors and the recession dummy and up market dummy variables. This effect is smaller in magnitude than the one found by Han, Yang and Zhou (2013). Note, however, that they use daily equal-weighted returns which could potentially explain the difference in the cross-sectional results between this study and their study.

Insert Table 5 here.

5.3 Conditional Models with Macroeconomic Variables

Ferson and Schadt (1996) make a strong case for using predetermined variables in controlling for changes in economic conditions while evaluating investment performance. I augment the four-factor Carhart (1997) model with an intercept that is a linear function of a set of instruments as well as cross-products of the instrumental variables with the market return to allow for state-dependent betas with the market factor. I use investor sentiment due to Baker and Wurgler (2006), the aggregate liquidity factor of Pastor and Stambaugh (2003), and the default spread of Moody's BAA corporate bond yield over the AAA corporate bond yield as the instrumental variables Z_t in the following regression:

$$\mathrm{MAP}_{jt,L} = \alpha_j + \beta_{j,m} r_{mkt,t} + \beta_{j,s} r_{smb,t} + \beta_{j,h} r_{hml,t} + \beta_{j,u} r_{umd,t} + \beta_{j,Z} Z_{t-1} + \gamma_{j,Z} Z_{t-1} r_{mkt,t} + \epsilon_{jt}, \quad j = 1, \ldots, N, \tag{10}$$

Baker and Wurgler (2006) provide evidence that investor sentiment is associated with expected returns and risks of the market. When investor sentiment is low, undervalued stocks are likely to be undervalued more strongly than when investor sentiment is high. Similarly, overvalued stocks are likely to be less overvalued when investor sentiment is low and more overvalued when investor sentiment is high. Next, I present evidence regarding the exposure of the MAP returns to changes in investor sentiment.

Table 9 presents the results of the conditional model estimation. Changes in investor sentiment are important both in increasing conditional alphas but also lead to higher betas with the market factor as evidenced by the positive coefficient estimate of the cross-product variable $\Delta S \times r_m$. Increases in the default spread result in higher conditional alphas but lower conditional betas with the market. The evidence for the aggregate liquidity factor is a little mixed and there appear to be some cross-sectional differences between the various decile portfolio returns. However, all the unconditional alphas for all sets of portfolios are highly statistically and economically significant. This suggests that investor sentiment, liquidity and especially the default premium can account for the MAP abnormal returns, at least using this particular conditional specification.

Finally, I put all the instrumental variables along with an NBER recession dummy variable in the same regression with the four Carhart (1997) factors as well as interactions between the instrumental variables and the market return. Table 6 presents the results from this conditional model specification. The previous results vis-a-vis investor sentiment, the default spread, and liquidity largely hold with the same signs albeit with a smaller degree of statistical significant. The recession indicator emerges as an important driver of conditional market betas where for all sets of portfolios the interaction term $RI \times r_m$ is always negative and highly statistically significant. This suggests that for almost all portfolios betas with the market tend to be significantly lower during economic recessions compared to their values during economic expansions.[11]

Insert Table 6 here.

5.4 Simulations

In this subsection, I report the results from two sets of simulations. First, I draw 1000 random samples designed to match the average historical return and the historical variance-covariance matrix of returns for each set of portfolios under consideration. Then, I compare the MA versus BH performance for every random sample and report the averages across all the simulations. Second, I draw randomly and without replacement 1000 samples from the historical returns. Again, I compare the performance of the MA strategy over the BH strategy for every bootstrapped sample and report the averages across all the simulations.

5.4.1 Randomly Generated Returns

Table 7 reports the average improvement in mean return and risk as well as the number of switches, percentage of months the MA strategy is invested in the underlying portfolio, break-even transaction costs, percentage of months the MA strategy return exceeds zero and the Treynor-Merton and Henriksson-Merton market timing alphas across 1000 Monte Carlo simulations designed to match the first two moments of the portfolio returns. Overall, the results are consistent with the results reported in previous sections regarding the various sets of portfolios. There is a significant improvement in both risk and return when comparing the moving average strategy over the buy-and-hold strategy. This improvement does not come at the cost of a lot of trading as the number of switches is between 47 (BM decile 8) and 67 (Momentum decile Low) from a total of 600 months in the entire sample period. The average break-even transaction costs are of similar order of magnitude as reported previously and indicate that the MA strategy is superior to the BH strategy for typical levels of proportional transaction costs available to both institutional and retail investors. Fully up to 2 out of 3 months the MA strategy delivers a positive return as indicated by the average value of p_1's reported in the table. Interestingly, virtually all of the market timing alphas are statistically significant. This is an indicator that the simulated returns produce MA returns that are not entirely explained by

[11] A further exercise involves including the MA indicator as an additional pre-specified instrumental variable as well as its interaction with the market return. The parameter estimates for these extra conditioning variables are highly significant and increase the goodness-of-fit of the predictive regressions. In the interest of saving space, these findings are not reported in the paper but are instead available from the author upon request. I am very grateful to a referee's suggestion for trying out this particular predictive variable.

market timing.

Insert Table 7 here.

What is apparent from these simulations is that what is needed for the superior performance of the MA strategy over the BH strategy is a time period of sufficient length and a positive drift of the underlying return. The randomly generated returns are completely independent of each other so all the autocorrelations and cross-autocorrelations are statistically insignificant from zero. The superior performance of the MA strategy does not appear to depend on any autocorrelation structure of the underlying returns.

Furthermore, the MA strategy appears to be antifragile in the sense of Taleb (2012). In other words, simulating returns with larger volatility will tend to sample the extreme tails of the return distribution and provide an even larger average return improvement. Clearly the improvement is diminishing as we increase the number of Monte Carlo simulations since the underlying data generation process is iid Gaussian and, thus, drawing extreme returns is highly unlikely.

5.4.2 Bootstrapped Returns

Table 8 reports average values across 1000 bootstrapped samples from the historical set of portfolio returns during the same period under consideration used in previous sections. As a starting point, I draw without replacement one monthly return[12] at random from the same sample for every single month and decile between 1960:01 and 2011:12. I run the moving average strategy and the buy-and-hold strategy for every simulated sample path and report the average improvement in mean return and standard deviation of return as well as the average number of switches, the average break-even transaction costs, percentage of positive returns and the average market timing alphas. The results are broadly consistent with the Monte Carlo simulation results reported previously as well as the decile portfolio results in Tables 3 and 4.

Insert Table 8 here.

Note once again the robustness of the results of the performance of the MA strategy vis-a-vis the BH strategy. Using a bootstrap window of one observation completely removes the autocorrelations from the bootstrapped sample. The fact that we still observe on improvement over BH suggests that return autocorrelations are not the main performance driver.

[12] In further unreported results I use a block bootstrap with various lengths of the block. The results are not materially different and are available from the author upon request.

5.5 Discussion

The large values of the risk-adjusted abnormal returns presented in the previous subsection demonstrate the profitability of the MA switching strategy. This raises the question as to what ultimately drives of the performance of the MA strategy. So far the evidence points towards a strategy that is contrarian, with a focus on large-cap growth stocks and short the market. However, the goodness-of-fit statistics indicate that this is at most only half the story. A more fundamental question that arises is how can this strategy survive in competitive financial markets. A few potential reasons seem plausible.

First, there is ample evidence that stock returns are predictable at various frequencies at least to a certain degree. This level of predictability is not perfect but is sufficient to improve forecasts of future stock returns when stock return predictability is ignored. Some of the early evidence presented in Fama and Schwert (1977) and Campbell (1987) as well as more recent work by Cochrane (2008) clearly demonstrates that stock return predictability is an important feature that investors should ignore at their own peril.

Evidence regarding the performance of the moving average technical indicator is present in Brock, Lakonishok and LeBaron (1992) in the context of predicting future moments of the Dow Jones Industrial Average. Lo, Mamaysky and Wang (2000) provide further evidence using a wide range of technical indicators with wide popularity among traders showing that this adds value even at the individual stock level over and above the performance of a stock index. More recently, Neely, Rapach, Tu, and Zhou (2010) provide evidence in favor of the usefulness of technical analysis in forecasting the stock market risk premium.

Second, early work on the performance of filter rules by Fama and Blume (1966), Jensen and Benington (1970) concluded that such rules were dominated by buy and hold strategies especially after transaction costs. Malkiel (1996) makes a forceful and memorable point against technical indicators: *"Obviously, I'm biased against the chartist. This is not only a personal predilection but a professional one as well. Technical analysis is anathema to the academic world. We love to pick on it. Our bullying tactics are prompted by two considerations: (1) after paying transaction costs, the method does not do better than a buy-and-hold strategy for investors, and (2) it's easy to pick on. And while it may seem a bit unfair to pick on such a sorry target, just remember: It's your money we are trying to save."* In a follow up on Brock et al (1992), Bessembinder and Chan (1998) attribute the forecasting power of technical analysis to measurement errors arising from non-synchronous trading. Ready (2002) goes even further and claims the results in Brock et al

(1992) are spurious and due to data snooping. Formal tests using White's Reality Check are conducted in Sullivan, Timmerman and White (1999) confirm that Brock et al (1992) results are robust to data snooping and perform even better out of sample though there is evidence of time variation in performance across subperiods. A more recent study using White's Reality Check and Hansen's SPA test is Hsu and Kuan (2005) who find evidence of profitability of technical analysis using relatively "young" markets like the NASDAQ Composite index and the Russell 2000 both in-sample and out-of-sample.

Furthermore, Treynor and Ferguson (1985) make a strong case in favor of investor's learning and Bayesian updating conditional on new information received rationally combining past prices can result in abnormal profitability. Sweeney (1988) revisits Fama and Blume (1966) and finds that filter rules can be profitable to floor traders in the 1970–1982 time period. Neftci (1991) presents a formal analysis of Wiener-Kolmogorov prediction theory which provides optimal linear forecasts. He concludes that if the underlying price processes are non-linear in nature then technical analysis rules might capture some useful information that is ignored by the linear prediction rules. More involved and inherently non-linear rules are investigated in the context of foreign currency exchange rates by Neely, Weller and Dittmar (1997) using a genetic programming approach. Gencay (1998) goes even further in using non-linear predictors based on simple moving average rules on the Dow Jones Industrial Average over a long time period between 1897 and 1988. In a similar vein, Allen and Karjalainen (1999) use genetic algorithms to search for functions of past prices find that can outperform a simple buy-and-hold strategy and report negative excess returns for most of the strategies they consider.

Thirdly, it is entirely possible that market prices of financial assets can persistently deviate from fundamental values. Those fundamental values themselves are subject to incomplete information and, perhaps, imperfect understanding of valuation tools as well as dispersion of beliefs and objective and behavioral biases across the pool of traders and investors who regularly interact in financial markets. When investors' information is incomplete and they learn continuously over time the true fundamental value, Zhu and Zhou (2009) show theoretically that the moving average price is a useful state variable that aids in investors' learning and improves their well-being and utility.

Behavioral and cognitive biases have been proposed in Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999), among others, as a potential driver of both price under- and over-reaction in conjunction with the observed price continuation of stock prices. An alternative explanation for price continuation was proposed in Zhang (2006). He argues that investors sub-optimally underweight newly arriving public information leading to a persistent deviation of the market price from the fundamental intrinsic value.

Note also that despite the apparent similarity of the MA switching strategy to the momentum strategy, the four-factor alphas reported previously are statistically significant and of large magnitudes. This is perhaps not surprising given that the payoff of the MA strategy resembles an at-the-money protective put strategy. The non-linearity this induces makes the asset pricing task much more difficult when linear models are used.

6 International Evidence

In this section, I investigate further the performance of the moving average strategy relative to the buy-and-hold strategy using stock returns from Australia, Canada, France, Germany, Italy, Japan and UK. In order to avoid the effects of exchange rate changes, I use local currency monthly returns for the entire stock market of each of the countries I consider as well as portfolio returns sorted on book-to-market, earnings yield, dividend yield and cash earnings to price ratio.

Table 9 reports the international evidence in favor of the moving average strategy. The findings are qualitatively and quantitatively similar to the findings reported previously for US portfolios. The MA strategy clearly outperforms the BH strategy and this outperformance is achieved with less risk. The MA strategy has a very low trading intensity with between 14 (UK Low DP and Low CEP portfolios) and 48 (Australia Low EP portfolio) switches in a sample of 432 months. Furthermore, the break-even transaction costs are large and well above realistic one-way transaction costs encountered in practice. Finally, the outperformance is larger for growth portfolios than for value portfolios. This is consistent with the protective put option explanation suggested previously since growth stocks are more volatile than value stocks.

Insert Table 9 here.

For the sake of consistency, I also investigate the performance of the moving average strategy using sets of six as well as 25 portfolios of international stocks sorted on size and momentum. For the sake of brevity I do not report these findings here but they are largely consistent with the results reported previously for other international portfolios as well as US portfolios.[13] As expected, riskier portfolios like small-caps and past losers tend to experience a larger return improvement via the moving average strategy compared to portfolios consisting of large-caps and past winners. Furthermore, the improved performance does not arise out of a large amount of trading. One notable difference is the slightly lower statistical significance of $\Delta\mu$. This is largely driven by the shorter sample of historical international portfolio returns. Nevertheless, the findings for international portfolios sorted on both size and momentum are consistent with the finding reported previously in this paper.

Finally, the value of the point estimate of the slope, measuring mean return improvement per unit BH portfolio risk, is remarkably consistent across the two sets of international portfolios when all regions of the world are considered jointly suggesting that a portfolio with 10% higher standard deviation will experience an average return improvement of between 3% to 4% when switching to the MA strategy relative to the BH strategy. This range of values is quite close to the value reported in (6) for US portfolios and slightly higher than the value reported in (8) for US individual stocks.

7 Conclusion

In this paper, I report results for a simple moving average switching strategy applied to decile portfolios sorted by size, book-to-market, and momentum. Further unreported findings for portfolios of stocks sorted by various measures of yield, past returns and industry classification support the reported findings. There is overwhelming evidence that the switching moving average strategy dominates in a mean-variance sense buying and holding any of the decile portfolios. The excess returns of the switching moving average returns over buying and holding the underlying portfolios are relatively insensitive to the four Carhart (1997) factors and generate high statistically and economically significant alphas. In addition, abnormal returns for most deciles decline substantially after controlling for investor sentiment, default, liquidity risks, recessions and up/down markets. This switching strategy does not involve any heavy trading when implemented with monthly returns and has very high break-even transaction costs, suggesting that it will be actionable even for small investors. The findings are robust with respect to portfolio construction, various lag lengths of the moving average, alternative sets of portfolios, international stock markets, individual stocks, randomly

[13] I am grateful to an anonymous referee for making this suggestion. The extended findings for these portfolios of international stocks are available from the author upon request.

generated stock returns and bootstrapped historical returns. Last but not least, the lagged signal indicating whether the price has crossed the simple moving average has substantial predictive power over the subsequent index return controlling for standard predictive variables like the default spread, investor sentiment, liquidity risk and economic conditions. The risk-adjusted performance disappears only in the context of market timing regressions in the framework of Henriksson-Merton (1981) where the downside market return is included as an additional factor and empirical asset pricing models with macroeconomic state variables. Hence, it appears that the success of the moving average strategy does not represent an anomaly and is consistent with rational asset pricing. In addition, any abnormal returns surviving the previously mentioned tests may not be actionable in practice due to limits to arbitrage and price impact of trading on illiquid risky assets with low trading volumes.[14]

Further work would be necessary to investigate the potential link between the returns of the MA switching strategy and the payoffs of protective put options on the underlying asset. A more aggressive implementation will involve selling short the underlying asset in response to a signal to switch instead of shifting the funds into cash. I conjecture that the payoff of this version of the MA strategy resembles an imperfect at-the-money straddle. It would also be of use to test more formally whether higher moments like skewness and kurtosis are improved by the MA strategy over the BH strategy. One potential alternative is to combine all first four moments using a utility function over them and convert the gains into certainty equivalent utility gains. Comparing those gain to the break-even transaction costs will provide further evidence into the superiority of the MA switching strategy.

Considering the vast literature on technical analysis and the numerous technical indicators following by some traders in practice, this study is just a first step towards investigating the performance and implementation of one common technical indicator. Future work will determine which other technical indicators perform well and whether they produce significant abnormal returns over and above the relevant transaction costs.

[14]A variant of the moving strategy using stock futures and interest rate futures (instead of trading the stock and the risk-free asset) could address this point in practice. I leave the study of this version of the moving average for future investigation.

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Table 1. Summary Statistics.

This table reports summary statistics for the respective buy and hold (BH) portfolio returns, the moving average (MA) switching strategy portfolio returns and the excess return of MA over BH (MAP) using sets of 10 portfolios sorted by size, book-to-market and momentum. The sample period covers 1960:01 until 2011:12 with value-weighted portfolio returns. μ is the annualized average return, σ is annualized standard deviation of returns, s is the annualized skewness, and SR is the annualized Sharpe ratio. The length of the moving average window is 24 months. A one-way transaction cost of 0.5% has been imposed in the computation of the MA and MAP returns.

Panel A: Size sorted portfolios.

Portfolio	μ	σ	s	SR	μ	σ	s	SR	μ	σ	s	SR
	BH Portfolios				MA Portfolios				MAP Portfolios			
Low	13.57	22.44	-0.14	0.38	17.94	17.04	0.35	0.75	4.37	14.09	0.71	0.31
2	12.92	22.28	-0.22	0.35	17.92	16.84	0.27	0.76	5.00	13.99	0.90	0.36
3	13.62	21.29	-0.41	0.40	17.62	16.25	0.03	0.77	4.00	13.24	1.21	0.30
4	13.01	20.52	-0.46	0.38	17.70	15.17	0.07	0.83	4.69	13.24	1.30	0.35
5	13.30	19.80	-0.48	0.41	17.48	14.66	-0.08	0.84	4.18	12.76	1.07	0.33
6	12.47	18.58	-0.49	0.40	16.59	13.73	0.08	0.84	4.11	11.99	1.38	0.34
7	12.50	18.26	-0.45	0.40	16.41	13.49	0.17	0.84	3.91	11.83	1.32	0.33
8	11.90	17.79	-0.43	0.38	15.91	13.24	0.14	0.82	4.01	11.36	1.34	0.35
9	11.19	16.35	-0.40	0.37	15.17	12.04	0.21	0.84	3.98	10.54	1.30	0.38
High	9.47	14.99	-0.31	0.29	13.11	11.70	-0.19	0.68	3.64	8.92	0.76	0.41
High−Low	-4.10	16.95	-0.74	-0.54	-4.83	16.35	-0.71	-0.61	-0.73	12.24	-0.66	-0.06

Panel B: Book-to-market sorted portfolios.

Portfolio	μ	σ	s	SR	μ	σ	s	SR	μ	σ	s	SR
	BH Portfolios				MA Portfolios				MAP Portfolios			
Low	9.13	18.13	-0.19	0.22	14.36	13.28	0.27	0.70	5.23	11.88	0.83	0.44
2	10.21	16.63	-0.43	0.31	14.38	12.67	0.12	0.73	4.17	10.28	1.65	0.41
3	10.95	16.26	-0.45	0.36	15.29	12.39	0.07	0.82	4.34	9.92	1.73	0.44
4	10.89	16.66	-0.46	0.35	14.80	12.14	0.37	0.80	3.91	10.93	1.58	0.36
5	10.76	15.66	-0.39	0.36	14.39	11.84	0.26	0.78	3.63	9.77	1.55	0.37
6	11.68	15.94	-0.40	0.41	15.26	12.17	0.31	0.83	3.58	9.77	1.71	0.37
7	12.31	15.53	-0.08	0.46	15.81	12.76	0.30	0.84	3.50	8.27	1.27	0.42
8	12.97	16.02	-0.44	0.49	15.47	12.42	0.14	0.83	2.50	9.70	1.43	0.26
9	13.93	16.90	-0.29	0.52	17.99	13.02	0.21	0.99	4.06	10.06	1.06	0.40
High	15.29	20.56	0.08	0.49	19.33	16.03	0.55	0.89	4.04	12.29	0.18	0.33
High−Low	6.16	16.17	0.54	0.06	4.97	15.13	0.72	-0.01	-1.19	11.45	-0.58	-0.10

Panel C: Momentum sorted portfolios.

Portfolio	μ	σ	s	SR	μ	σ	s	SR	μ	σ	s	SR
	BH Portfolios				MA Portfolios				MAP Portfolios			
Low	1.23	28.02	0.67	-0.14	11.90	13.53	1.10	0.50	10.68	24.14	-1.00	0.44
2	7.82	21.88	0.24	0.12	13.39	14.19	0.62	0.58	5.57	16.26	-0.43	0.34
3	9.30	18.80	0.33	0.22	13.94	12.33	0.59	0.72	4.64	13.82	-0.79	0.34
4	9.97	16.93	-0.11	0.29	13.77	11.62	0.53	0.74	3.80	11.92	0.34	0.32
5	8.96	15.69	-0.25	0.25	12.89	10.99	0.42	0.71	3.93	10.72	0.83	0.37
6	10.14	15.92	-0.36	0.32	14.27	11.64	0.55	0.79	4.13	10.38	1.62	0.40
7	10.41	15.42	-0.48	0.34	14.23	12.00	0.12	0.76	3.82	9.17	2.14	0.42
8	12.60	15.77	-0.29	0.47	15.25	13.12	-0.08	0.77	2.65	8.31	1.11	0.32
9	13.21	17.05	-0.52	0.47	16.40	14.32	-0.10	0.79	3.19	8.72	2.90	0.37
High	17.62	21.78	-0.39	0.57	21.58	18.69	-0.07	0.88	3.96	10.46	2.57	0.38
High−Low	16.39	24.17	-1.52	0.47	9.68	17.97	-0.41	0.25	-6.72	20.90	1.90	-0.32

Table 2. Factor Regressions Results.

This table reports alphas, betas, and adjusted R^2 of the regressions of the MAP excess returns on the Carhart four-factors using portfolios sorted by size, book-to-market and momentum. The alphas are annualized and in percent. The sample period covers 1960:01 until 2011:12 with value-weighted portfolio returns. The length of the moving average window is 24 months. A one-way transaction cost of 0.5% has been imposed in constructing the switching moving average strategy excess returns. Newey and West (1987) standard errors with 24 lags are used in reporting statistical significance of a two-sided null hypothesis at the 1%, 5%, and 10% level is given by a ***, a **, and a *, respectively.

Panel A: Size sorted portfolios.

Portfolio	α	β_m	β_s	β_h	β_u	$\bar{R}^2$
Low	6.04***	-0.46***	-0.36***	-0.13***	0.27***	53.01
2	6.94***	-0.48***	-0.33***	-0.19***	0.27***	54.23
3	5.41***	-0.46***	-0.27***	-0.11***	0.25***	51.32
4	6.36***	-0.47***	-0.27***	-0.12***	0.24***	52.80
5	4.99***	-0.46***	-0.21***	-0.05	0.27***	54.53
6	5.10***	-0.44***	-0.17***	-0.03	0.22***	52.86
7	5.22***	-0.45***	-0.14***	-0.09***	0.20***	50.85
8	5.20***	-0.44***	-0.10***	-0.08***	0.20***	51.11
9	5.17***	-0.43***	-0.05**	-0.07**	0.17***	50.58
High	3.35***	-0.33***	0.07***	0.06***	0.17***	46.29
High−Low	2.69***	-0.13***	-0.43***	-0.19***	0.10***	21.83

Panel B: Book-to-market sorted portfolios.

Portfolio	α	β_m	β_s	β_h	β_u	$\bar{R}^2$
Low	4.49***	-0.45***	0.07***	0.21***	0.21***	51.97
2	4.88***	-0.38***	-0.03	0.02	0.14***	42.86
3	5.52***	-0.39***	-0.06***	-0.02	0.12***	46.44
4	5.87***	-0.45***	-0.05**	-0.16***	0.14***	49.35
5	5.22***	-0.39***	-0.03	-0.14***	0.13***	44.62
6	5.13***	-0.38***	-0.06**	-0.14***	0.14***	45.83
7	4.41***	-0.29***	0.03	-0.13***	0.13***	37.14
8	4.59***	-0.35***	-0.06**	-0.27***	0.14***	42.04
9	5.75***	-0.37***	-0.08***	-0.21***	0.17***	45.86
High	5.83***	-0.42***	-0.12***	-0.23***	0.20***	40.56
High−Low	-1.34	-0.04	0.19***	0.44***	0.00	15.23

Panel C: Momentum sorted portfolios.

Portfolio	α	β_m	β_s	β_h	β_u	$\bar{R}^2$
Low	7.44***	-0.84***	-0.26***	0.20***	0.84***	71.75
2	4.75***	-0.56***	-0.11***	-0.08*	0.51***	60.02
3	3.13**	-0.45***	0.00	-0.02	0.45***	56.64
4	4.18***	-0.45***	-0.00	-0.08***	0.27***	50.88
5	5.09***	-0.43***	-0.00	-0.11***	0.18***	48.14
6	5.25***	-0.42***	-0.02	-0.05*	0.15***	48.84
7	5.19***	-0.36***	0.01	-0.04*	0.07***	39.95
8	4.01***	-0.32***	0.00	-0.06***	0.07***	39.01
9	5.28***	-0.34***	0.01	-0.08***	-0.00	34.56
High	5.95***	-0.39***	-0.01	-0.01	0.01	34.30
High−Low	1.49	-0.45***	-0.26***	0.21***	0.83***	57.68

Table 3. Trading Frequency and Break-Even Transaction Cost.

This table reports the results for the improvement delivered by the MA switching strategy over the buy-and-hold strategy, the trading frequency as well as the break-even transaction cost using ten decile portfolios sorted by size, book-to-market and momentum. The sample period covers 1960:01 until 2011:12 with value-weighted portfolio returns. $\Delta\mu$ is the annualized improvement in the average in-sample monthly return, $\Delta\sigma$ is the annualized improvement in the return standard deviation, p_A is the proportion of months during which there is a hold signal, NT is the number of transactions (buy or sell) over the entire sample period, BETC is the break-even one-sided transaction cost in percent, p_1 is the proportion of months during which a buy signal was followed by a positive return of the underlying portfolio and p_2 is the proportion of months during which a buy signal was followed by a portfolio return in excess of the risk-free rate. The length of the moving average window is 24 months. A one-way transaction cost of 0.5% has been imposed in the reported $\Delta\mu$ and $\Delta\sigma$. Statistical significance of the one-sided null hypotheses that $\Delta\mu > 0$, $\Delta\sigma > 0$, $p_1 > 0.5$ and $p_2 > 0.5$ at the 1%, 5%, and 10% level is given by a ***, a **, and a *, respectively.

Panel A: Size sorted portfolios.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1	p_2
Low	4.37**	5.40***	0.74	39	5.60	0.60***	0.57***
2	5.00***	5.44***	0.77	46	5.43	0.57***	0.55***
3	4.00**	5.05***	0.80	44	4.55	0.59***	0.57***
4	4.69***	5.35***	0.79	50	4.69	0.59***	0.56***
5	4.18**	5.14***	0.80	44	4.75	0.61***	0.57***
6	4.11***	4.85***	0.80	38	5.41	0.60***	0.56***
7	3.91***	4.77***	0.81	32	6.11	0.60***	0.57***
8	4.01***	4.55***	0.81	42	4.77	0.60***	0.56***
9	3.98***	4.31***	0.81	42	4.74	0.59***	0.57***
High	3.64***	3.29***	0.80	38	4.79	0.61***	0.57***

Panel B: Book-to-market sorted portfolios.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1	p_2
Low	5.23***	4.86***	0.72	42	6.22	0.57***	0.54**
2	4.17***	3.97***	0.81	44	4.74	0.58***	0.56***
3	4.34***	3.86***	0.79	50	4.34	0.60***	0.56***
4	3.91***	4.52***	0.80	40	4.88	0.60***	0.58***
5	3.63***	3.82***	0.82	30	6.04	0.62***	0.58***
6	3.58***	3.78***	0.84	38	4.71	0.61***	0.56***
7	3.50***	2.78***	0.84	34	5.15	0.62***	0.58***
8	2.50**	3.60***	0.86	36	3.47	0.62***	0.58***
9	4.06***	3.88***	0.84	44	4.61	0.63***	0.59***
High	4.04**	4.53***	0.83	29	6.96	0.62***	0.58***

Panel C: Momentum sorted portfolios.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1	p_2
Low	10.68***	14.49***	0.58	69	7.74	0.50	0.46**
2	5.57***	7.69***	0.76	44	6.33	0.55**	0.51
3	4.64***	6.48***	0.76	44	5.27	0.56***	0.52
4	3.80**	5.31***	0.80	42	4.52	0.57***	0.53*
5	3.93***	4.70***	0.80	52	3.78	0.58***	0.55***
6	4.13***	4.28***	0.78	38	5.43	0.58***	0.56***
7	3.82***	3.42***	0.80	44	4.34	0.61***	0.57***
8	2.65**	2.65***	0.81	38	3.49	0.62***	0.58***
9	3.19***	2.73***	0.82	32	4.98	0.63***	0.60***
High	3.96***	3.09***	0.81	41	4.83	0.63***	0.60***

Table 4. Market Timing Regressions: Monthly Decile Portfolios.

This table reports alphas, betas, and adjusted R^2 of the market timing regressions of the MAP excess returns on the market factor using portfolios sorted by size, book-to-market and momentum. The TM panel reports the results using the Treynor and Mazuy (1966) quadratic regression with the squared market factor (β_{m^2}) while the HM panel reports the results using the Henriksson and Merton (1981) regression with option-like returns on the market (γ_m). The sample period covers 1960:01 until 2011:12 with value-weighted portfolio returns. The length of the moving average window is 24 months. A one-way transaction cost of 0.5% has been imposed in constructing the switching moving average strategy excess returns. Newey and West (1987) standard errors with 24 lags are used in reporting statistical significance of a two-sided null hypothesis at the 1%, 5%, and 10% level is given by a ***, a **, and a *, respectively.

Panel A: Size sorted portfolios.

Portfolio	α	β_m	β_{m^2}	$\bar{R}^2$	α	β_m	γ_m	$\bar{R}^2$
	TM				HM			
Low	2.19	-0.52***	0.02***	41.20	-1.67	-0.75***	0.41***	39.97
2	2.53*	-0.52***	0.02***	42.50	-1.86	-0.77***	0.45***	41.27
3	0.89	-0.49***	0.02***	44.08	-4.09***	-0.77***	0.50***	42.54
4	1.50	-0.50***	0.02***	46.46	-3.97**	-0.79***	0.54***	45.11
5	1.37	-0.49***	0.02***	47.19	-3.33**	-0.75***	0.48***	45.67
6	1.08	-0.47***	0.02***	49.83	-4.32***	-0.75***	0.52***	48.54
7	1.12	-0.46***	0.02***	47.78	-3.81**	-0.72***	0.48***	46.49
8	1.43	-0.44***	0.02***	48.24	-3.47***	-0.69***	0.46***	47.19
9	1.59*	-0.42***	0.02***	49.68	-3.09**	-0.65***	0.44***	48.71
High	4.38***	-0.34***	0.00***	38.59	0.19	-0.47***	0.25***	40.16
High−Low	-2.20	-0.18***	0.02***	9.20	-1.86	-0.28***	0.17**	6.82

Panel B: Book-to-market sorted portfolios.

Portfolio	α	β_m	β_{m^2}	$\bar{R}^2$	α	β_m	γ_m	$\bar{R}^2$
	TM				HM			
Low	4.42***	-0.48***	0.01***	46.44	-0.10	-0.68***	0.37***	46.72
2	1.76*	-0.38***	0.02***	44.28	-2.81**	-0.61***	0.43***	43.40
3	2.13***	-0.39***	0.02***	48.20	-2.78**	-0.62***	0.43***	47.84
4	1.13	-0.43***	0.02***	48.84	-3.51**	-0.67***	0.46***	47.33
5	1.32	-0.36***	0.02***	43.61	-2.33*	-0.56***	0.37***	42.05
6	0.55	-0.36***	0.02***	45.41	-3.56***	-0.59***	0.43***	43.11
7	3.75***	-0.27***	0.00**	28.24	0.29	-0.38***	0.22***	29.46
8	0.78	-0.31***	0.01***	32.00	-2.30*	-0.48***	0.30***	31.11
9	1.36*	-0.35***	0.02***	40.03	-3.57***	-0.59***	0.45***	39.30
High	1.46	-0.40***	0.02***	33.52	-2.73*	-0.62***	0.42***	32.38
High−Low	2.97*	-0.09***	-0.01*	1.22	2.62	-0.05	-0.05	0.86

Panel C: Momentum sorted portfolios.

Portfolio	α	β_m	β_{m^2}	$\bar{R}^2$	α	β_m	γ_m	$\bar{R}^2$
	TM				HM			
Low	14.80***	-1.03***	0.00	45.82	12.85***	-1.11***	0.14	45.85
2	8.80***	-0.64***	-0.00	37.83	5.66***	-0.71***	0.15**	38.04
3	7.35***	-0.51***	-0.00	33.38	4.22***	-0.57***	0.14***	33.64
4	2.49**	-0.45***	0.01***	41.47	-1.72	-0.65***	0.37***	41.29
5	1.51	-0.40***	0.02***	45.18	-3.17**	-0.64***	0.44***	44.30
6	0.71	-0.40***	0.02***	51.94	-4.89***	-0.69***	0.53***	50.39
7	1.24	-0.34***	0.02***	44.76	-3.63***	-0.57***	0.44***	44.12
8	1.40**	-0.30***	0.01***	40.19	-1.65	-0.45***	0.28***	39.74
9	-0.10	-0.30***	0.02***	42.90	-4.51***	-0.53***	0.44***	40.51
High	1.63**	-0.37***	0.02***	39.19	-3.23***	-0.60***	0.43***	38.83
High−Low	13.17***	-0.66***	-0.01***	24.23	16.08***	-0.51***	-0.29***	24.06

Table 5. Factor Regressions with Business Cycles and Up Markets: Monthly Decile Portfolios.

This table reports alphas, betas, and adjusted R^2 of the factor regressions of the MAP excess returns using the Carhart four-factor model with NBER recession indicator dummy variable (RI) and up market indicators (UP) using portfolios sorted by size, book-to-market and momentum. Alphas are annualized and in percent. The sample period covers 1960:01 until 2011:12 with value-weighted portfolio returns. The length of the moving average window is 24 months. A one-way transaction cost of 0.5% has been imposed in constructing the switching moving average strategy excess returns. Newey and West (1987) standard errors with 24 lags are used in reporting statistical significance of a two-sided null hypothesis at the 1%, 5%, and 10% level is given by a ***, a **, and a *, respectively.

Panel A: Size sorted portfolios.

Portfolio	α	β_m	β_s	β_h	β_u	RI	$\bar{R}^2$	α	β_m	β_s	β_h	β_u	UP	$\bar{R}^2$
	Recession Dummy							Up Market Dummy						
Low	4.95***	-0.46***	-0.36***	-0.13***	0.27***	0.58**	53.18	-6.11***	-0.62***	-0.37***	-0.13***	0.26***	1.88***	54.97
2	5.94***	-0.48***	-0.33***	-0.18***	0.27***	0.53**	54.36	-5.47***	-0.64***	-0.34***	-0.19***	0.26***	1.92***	56.32
3	4.51***	-0.45***	-0.27***	-0.11***	0.25***	0.48**	51.43	-8.20***	-0.63***	-0.27***	-0.11***	0.24***	2.10***	54.17
4	5.63***	-0.47***	-0.27***	-0.12***	0.24***	0.39**	52.85	-6.57***	-0.64***	-0.27***	-0.12***	0.22***	2.00***	55.37
5	3.85***	-0.45***	-0.21***	-0.05*	0.27***	0.60***	54.79	-7.80***	-0.62***	-0.22***	-0.05*	0.26***	1.98***	57.25
6	4.26***	-0.44***	-0.17***	-0.03	0.22***	0.44***	52.99	-7.52***	-0.61***	-0.18***	-0.03	0.21***	1.95***	55.86
7	4.12***	-0.44***	-0.14***	-0.08***	0.21***	0.58***	51.13	-7.55***	-0.61***	-0.15***	-0.08***	0.19***	1.97***	54.01
8	4.18***	-0.44***	-0.10***	-0.08***	0.20***	0.53***	51.36	-6.57***	-0.59***	-0.10***	-0.08***	0.19***	1.82***	54.01
9	4.52***	-0.42***	-0.05**	-0.07***	0.17***	0.35*	50.66	-6.40***	-0.57***	-0.06**	-0.07***	0.16***	1.79***	53.86
High	2.35***	-0.33***	0.07***	0.06***	0.17***	0.53***	46.73	-2.80**	-0.41***	0.07***	0.06***	0.16***	0.95***	47.47
High−Low	2.60**	-0.13***	-0.43***	-0.19***	0.10***	0.05	21.70	-3.31*	-0.21***	-0.44***	-0.19***	0.09***	0.93***	22.26

Panel B: Book-to-market sorted portfolios.

Portfolio	α	β_m	β_s	β_h	β_u	RI	$\bar{R}^2$	α	β_m	β_s	β_h	β_u	UP	$\bar{R}^2$
	Recession Dummy							Up Market Dummy						
Low	3.40***	-0.45***	0.07***	0.21***	0.21***	0.57***	52.25	-4.40**	-0.57***	0.07***	0.21***	0.20***	1.37***	53.41
2	3.99***	-0.37***	-0.03	0.02	0.14***	0.47**	43.08	-5.46***	-0.51***	-0.04	0.02	0.13***	1.60***	45.56
3	4.86***	-0.39***	-0.06***	-0.02	0.12***	0.35**	46.53	-5.06***	-0.53***	-0.06***	-0.02	0.11***	1.63***	49.51
4	5.33***	-0.45***	-0.05**	-0.16***	0.14***	0.28	49.37	-5.98***	-0.61***	-0.06**	-0.16***	0.13***	1.83***	52.54
5	4.51***	-0.38***	-0.03	-0.14***	0.13***	0.37**	44.75	-4.63***	-0.52***	-0.03	-0.14***	0.12***	1.52***	47.34
6	3.98***	-0.37***	-0.06***	-0.14***	0.14***	0.61***	46.32	-6.24***	-0.53***	-0.07***	-0.14***	0.13***	1.75***	49.51
7	2.85***	-0.28***	0.03	-0.13***	0.13***	0.82***	38.54	0.59	-0.34***	0.03	-0.13***	0.13***	0.59**	37.54
8	3.81***	-0.35***	-0.06***	-0.27***	0.14***	0.41**	42.21	-5.01***	-0.48***	-0.06***	-0.27***	0.13***	1.48***	44.64
9	5.02***	-0.37***	-0.08***	-0.21***	0.17***	0.38*	45.99	-4.32**	-0.50***	-0.09***	-0.21***	0.16***	1.55***	48.54
High	4.91***	-0.41***	-0.12***	-0.23***	0.21***	0.49*	40.70	-4.19*	-0.55***	-0.13***	-0.23***	0.19***	1.55***	42.27
High−Low	-1.51	-0.03	0.19***	0.44***	0.00	0.09	15.09	-0.21	-0.02	0.19***	0.44***	0.01	-0.17	14.97

Panel C: Momentum sorted portfolios.

Portfolio	α	β_m	β_s	β_h	β_u	RI	$\bar{R}^2$	α	β_m	β_s	β_h	β_u	UP	$\bar{R}^2$
	Recession Dummy							Up Market Dummy						
Low	7.33***	-0.83***	-0.26***	0.20***	0.84***	0.06	71.70	-0.55	-0.94***	-0.27***	0.20***	0.83***	1.23***	71.97
2	3.35***	-0.55***	-0.11***	-0.08***	0.51***	0.74***	60.27	-3.49	-0.67***	-0.12***	-0.08**	0.50***	1.27***	60.62
3	1.93**	-0.45***	0.00	-0.02	0.45***	0.63***	56.88	-2.84*	-0.53***	-0.00	-0.02	0.45***	0.92***	57.02
4	3.92***	-0.45***	-0.00	-0.08***	0.27***	0.13	50.81	-7.51***	-0.60***	-0.01	-0.08***	0.26***	1.80***	53.46
5	4.66***	-0.43***	-0.00	-0.11***	0.18***	0.23	48.12	-6.21***	-0.57***	-0.01	-0.11***	0.17***	1.75***	51.15
6	4.94***	-0.42***	-0.02	-0.05**	0.15***	0.17	48.79	-6.81***	-0.58***	-0.03	-0.05*	0.14***	1.86***	52.52
7	4.70***	-0.36***	0.01	-0.04*	0.07***	0.26	39.96	-5.40***	-0.50***	0.00	-0.04	0.06***	1.63***	43.55
8	3.46***	-0.32***	0.00	-0.06***	0.07***	0.29*	39.09	-5.10***	-0.44***	-0.00	-0.06***	0.06***	1.41***	42.24
9	4.36***	-0.34***	0.01	-0.07***	-0.00	0.49**	34.92	-4.91***	-0.47***	0.01	-0.08***	-0.01	1.57***	38.24
High	4.88***	-0.38***	-0.01	-0.01	0.01	0.56***	34.62	-5.42***	-0.54***	-0.01	-0.01	-0.01	1.75***	37.45
High−Low	2.45	-0.45***	-0.25***	0.21***	0.83***	-0.51	57.70	4.86*	-0.40***	-0.25***	0.21***	0.83***	-0.52	57.61

Table 6. Conditional Regressions with Investor Sentiment, Default Spread, Liquidity Factor, and Recession Dummy.

This table reports alphas, betas, and adjusted R^2 of the market timing regressions of the MAP excess returns on the four Carhart factors plus one instrumental variable (change in investor sentiment ΔS from Baker and Wurgler (2007), default spread D using the difference between Moody's BAA and AAA corporate bond yields, liquidity factor L from Pastor and Stambaugh (2003), and a recession dummy RI) as well as interaction terms of the instrumental variable with the market's excess return using portfolios sorted by size, book-to-market and momentum. Alphas are annualized and in percent. The sample period covers 1968:08 until 2010:12. The length of the moving average window is 24 months. A one-way transaction cost of 0.5% has been imposed in constructing the switching moving average strategy excess returns. Newey and West (1987) standard errors with 24 lags are used in reporting statistical significance of a two-sided null hypothesis at the 1%, 5%, and 10% level is given by a ***, a **, and a *, respectively.

Panel A: Size sorted portfolios.

Portfolio	α	ΔS	D	L	RI	$\Delta S \times r_m$	$D \times r_m$	$L \times r_m$	$RI \times r_m$	$\bar{R}^2$
Low	-0.64	0.31***	0.37	-3.76	-0.03	0.07***	-0.05	-0.02	-0.30***	57.35
2	1.54	0.36***	0.34	-3.92	-0.15	0.05***	0.01	-0.44	-0.37***	60.12
3	-1.96	0.30***	0.47**	-7.34***	-0.19	0.07***	-0.03	-0.37	-0.39***	58.49
4	-0.93	0.24***	0.47**	-6.25***	-0.35	0.07***	0.05	-0.40	-0.39***	58.67
5	-2.86	0.16*	0.48***	-5.57***	-0.03	0.07***	0.03	-0.60*	-0.43***	61.97
6	-2.30	0.16**	0.41**	-6.24***	-0.14	0.07***	0.07**	-0.47	-0.42***	59.30
7	-0.44	0.18**	0.29*	-7.51***	0.15	0.05***	0.03	-0.09	-0.49***	60.23
8	-2.61	0.19**	0.46***	-6.30***	0.06	0.05***	0.05*	0.04	-0.49***	60.35
9	1.23	0.16**	0.16	-3.01	0.05	0.06***	-0.02	0.16	-0.46***	62.76
High	-3.39*	-0.08	0.30**	-0.84	0.21	0.05***	-0.01	-0.12	-0.42***	58.34
High−Low	2.76	0.39***	0.07	-2.92	-0.24	0.02	-0.04	0.10	0.12**	22.34

Panel B: Book-to-market sorted portfolios.

Portfolio	α	ΔS	D	L	RI	$\Delta S \times r_m$	$D \times r_m$	$L \times r_m$	$RI \times r_m$	$\bar{R}^2$
Low	-4.41*	-0.11	0.48***	-3.09	-0.13	0.11***	-0.06**	-0.86**	-0.49***	64.67
2	-0.89	0.22**	0.29	-2.63	0.07	0.06***	-0.01	0.12	-0.30***	48.29
3	3.84*	0.27***	-0.01	-1.06	-0.02	0.05***	0.12***	-1.14***	-0.45***	55.94
4	1.62	0.19**	0.17	-3.91*	0.06	0.07***	-0.15***	-0.65*	-0.24***	55.83
5	2.32	0.09	0.08	-2.20	0.24	0.07***	-0.10***	-0.66*	-0.27***	53.03
6	-2.54	0.19**	0.45***	-5.26***	0.33	0.03***	-0.11***	-0.11	-0.30***	56.00
7	-1.67	0.15*	0.26	-0.06	0.79***	0.01	-0.02	1.19***	-0.32***	50.62
8	-5.23**	0.20**	0.65***	-0.43	0.07	0.01	-0.24***	-1.08***	-0.27***	57.28
9	0.30	0.19*	0.34	-4.65*	0.10	0.02	-0.07*	-0.91**	-0.27***	52.65
High	-3.43	0.35**	0.53*	5.58*	0.39	0.01	-0.31***	1.05**	-0.17***	49.49
High−Low	-0.98	-0.46***	-0.05	-8.67***	-0.51	0.11***	0.24***	-1.90***	-0.32***	25.98

Panel C: Momentum sorted portfolios.

Portfolio	α	ΔS	D	L	RI	$\Delta S \times r_m$	$D \times r_m$	$L \times r_m$	$RI \times r_m$	$\bar{R}^2$
Low	3.35	-0.44***	0.24	-1.38	-0.50	0.07***	-0.11**	-1.12**	-0.48***	75.19
2	0.93	0.10	0.07	-5.19**	0.50*	0.03**	-0.09**	0.50	-0.69***	70.78
3	0.53	-0.11	0.03	-4.01**	0.51**	0.00	0.05*	0.62**	-0.64***	66.58
4	-1.10	0.35***	0.26	0.65	-0.17	0.05***	-0.02	0.04	-0.45***	58.80
5	3.13	0.21**	0.00	4.09**	-0.05	0.06***	-0.04	-0.79**	-0.42***	59.09
6	4.72**	0.16**	-0.12	0.71	-0.08	0.09***	-0.04	-1.16***	-0.37***	59.41
7	2.11	0.17**	0.02	3.24	0.02	0.09***	-0.00	-0.34	-0.33***	46.78
8	-3.12	0.20***	0.43***	0.22	-0.13	0.05***	-0.03	0.13	-0.33***	48.83
9	0.13	0.09	0.23	-4.73**	0.12	0.08***	-0.03	-0.35	-0.35***	45.08
High	-1.76	0.01	0.36**	-0.67	0.07	0.12***	-0.06*	-0.29	-0.39***	44.92
High−Low	5.12	-0.45***	-0.12	-0.71	-0.57	-0.05**	-0.05	-0.83	-0.09	59.32

Table 7. Monte Carlo Simulations.

This table reports the results for the improvement delivered by the MA switching strategy over the buy-and-hold strategy, the trading frequency as well as the break-even transaction cost using 1000 Monte Carlo simulations with randomly generated returns designed to match the first two moments of ten decile portfolios sorted by size, book-to-market and momentum. The sample period covers 1960:01 until 2011:12 with value-weighted portfolio returns. $\Delta\mu$ is the annualized improvement in the average in-sample monthly return, $\Delta\sigma$ is the annualized improvement in the return standard deviation, p_A is the proportion of months during which there is a hold signal, NT is the number of transactions (buy or sell) over the entire sample period, BETC is the break-even one-sided transaction cost in percent, and p_1 is the proportion of months during which a buy signal was followed by a positive return of the underlying portfolio. The length of the moving average window is 24 months. A one-way transaction cost of 0.5% has been imposed in the reported $\Delta\mu$ and $\Delta\sigma$.

Panel A: Size sorted portfolios.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
Low	6.233	3.957	0.717	58.550	5.393	0.696
2	6.397	4.054	0.709	59.572	5.447	0.698
3	5.616	3.504	0.737	56.110	5.064	0.691
4	5.483	3.395	0.736	56.769	4.878	0.691
5	5.036	3.099	0.751	54.798	4.657	0.688
6	4.718	2.860	0.756	54.165	4.405	0.686
7	4.515	2.735	0.763	53.271	4.287	0.685
8	4.493	2.701	0.760	53.611	4.247	0.685
9	4.048	2.397	0.769	52.421	3.910	0.683
High	4.094	2.383	0.751	54.835	3.785	0.685

Panel B: Book-to-market sorted portfolios.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
Low	5.873	3.557	0.688	61.167	4.868	0.701
2	4.570	2.711	0.741	55.712	4.155	0.688
3	4.077	2.412	0.766	53.354	3.880	0.683
4	4.347	2.591	0.755	54.129	4.072	0.686
5	3.741	2.202	0.780	50.998	3.709	0.681
6	3.736	2.209	0.784	50.408	3.738	0.681
7	3.324	1.955	0.805	47.599	3.542	0.677
8	3.335	1.981	0.808	47.060	3.575	0.677
9	3.451	2.066	0.809	46.743	3.718	0.677
High	4.770	2.951	0.773	51.940	4.635	0.685

Panel C: Momentum sorted portfolios.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
Low	14.519	9.904	0.450	67.526	11.113	0.776
2	8.422	5.366	0.610	65.728	6.548	0.724
3	6.120	3.744	0.683	61.190	5.080	0.703
4	5.015	2.976	0.723	57.578	4.428	0.693
5	4.621	2.708	0.728	57.089	4.099	0.692
6	4.264	2.519	0.751	54.078	3.986	0.687
7	3.986	2.337	0.763	52.913	3.818	0.684
8	3.391	1.986	0.804	47.714	3.576	0.677
9	3.671	2.185	0.800	48.301	3.843	0.679
High	4.419	2.763	0.801	48.140	4.624	0.681

Table 8. Bootstrap Simulations.

This table reports the results for the improvement delivered by the MA switching strategy over the buy-and-hold strategy, the trading frequency as well as the break-even transaction cost using 1000 bootstrap simulations with randomly drawn returns from the historical returns of ten decile portfolios sorted by size, book-to-market and momentum. The sample period covers 1960:01 until 2011:12 with value-weighted portfolio returns. $\Delta\mu$ is the annualized improvement in the average in-sample monthly return, $\Delta\sigma$ is the annualized improvement in the return standard deviation, p_A is the proportion of months during which there is a hold signal, NT is the number of transactions (buy or sell) over the entire sample period, BETC is the break-even one-sided transaction cost in percent, and p_1 is the proportion of months during which a buy signal was followed by a positive return of the underlying portfolio. The length of the moving average window is 24 months. A one-way transaction cost of 0.5% has been imposed in the reported $\Delta\mu$ and $\Delta\sigma$.

Panel A: Size sorted portfolios.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
Low	5.999	4.355	0.728	53.025	5.810	0.713
2	6.168	4.524	0.718	54.910	5.752	0.705
3	5.531	4.188	0.746	52.878	5.362	0.705
4	5.388	4.093	0.745	53.250	5.197	0.705
5	5.017	3.799	0.759	51.736	4.972	0.709
6	4.691	3.509	0.764	51.186	4.698	0.700
7	4.462	3.351	0.771	49.830	4.601	0.700
8	4.445	3.244	0.767	50.777	4.493	0.698
9	3.999	2.869	0.777	49.728	4.129	0.690
High	4.084	2.764	0.757	51.564	4.067	0.712

Panel B: Book-to-market sorted portfolios.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
Low	5.801	3.890	0.695	58.149	5.121	0.709
2	4.566	3.252	0.748	52.523	4.462	0.697
3	4.098	2.958	0.772	49.318	4.268	0.702
4	4.353	3.191	0.761	49.777	4.504	0.701
5	3.742	2.717	0.785	46.914	4.097	0.711
6	3.720	2.737	0.791	46.224	4.131	0.698
7	3.292	2.170	0.810	44.465	3.794	0.700
8	3.390	2.648	0.814	41.779	4.171	0.695
9	3.506	2.496	0.813	43.614	4.132	0.707
High	4.574	3.386	0.782	46.153	5.088	0.707

Panel C: Momentum sorted portfolios.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
Low	14.009	8.645	0.447	62.438	11.525	0.777
2	8.029	5.226	0.616	60.257	6.848	0.724
3	5.769	3.643	0.689	55.939	5.302	0.698
4	4.825	3.219	0.729	53.356	4.643	0.696
5	4.517	3.073	0.737	53.093	4.375	0.702
6	4.236	2.992	0.759	50.717	4.291	0.697
7	3.973	2.881	0.772	49.665	4.109	0.710
8	3.399	2.378	0.810	44.976	3.875	0.702
9	3.678	2.819	0.807	44.727	4.218	0.710
High	4.464	3.455	0.805	45.275	5.044	0.709

Table 9. International Evidence of Moving Average Strategies Performance.

This table reports the results for the improvement delivered by the MA switching strategy over the buy-and-hold strategy, the trading frequency as well as the break-even transaction cost using local currency value-weighted returns of the market portfolios and portfolios sorted by several variables in seven countries. $\Delta\mu$ is the annualized improvement in the average in-sample monthly return, $\Delta\sigma$ is the annualized improvement in the return standard deviation, p_A is the proportion of months during which there is a hold signal, NT is the number of transactions (buy or sell) over the entire sample period, BETC is the break-even one-sided transaction cost in percent, and p_1 is the proportion of months during which a buy signal was followed by a positive return of the underlying portfolio. The length of the moving average window is 24 months. A one-way transaction cost of 0.5% has been imposed in the reported $\Delta\mu$ and $\Delta\sigma$.

Panel A: Australian portfolios between 1975:01 and 2010:12.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
MKT	4.253	3.711	0.828	30	4.820	0.711
High BM	2.770	3.800	0.880	20	4.710	0.716
Low BM	5.647	5.607	0.740	38	5.052	0.686
High EP	2.537	3.325	0.900	18	4.793	0.725
Low EP	6.457	5.674	0.723	48	4.574	0.701
High CEP	1.685	1.708	0.897	24	2.387	0.681
Low CEP	7.608	6.423	0.676	42	6.159	0.708
High DP	1.726	1.778	0.904	16	3.667	0.708
Low DP	6.178	5.721	0.757	36	5.835	0.686
Zero DP	11.449	10.351	0.564	42	9.268	0.735

Panel B: Canadian portfolios between 1977:01 and 2010:12.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
MKT	3.409	3.959	0.805	26	4.195	0.706
High BM	4.189	3.714	0.818	26	5.155	0.690
Low BM	5.881	5.300	0.737	40	4.704	0.698
High EP	2.943	3.727	0.865	22	4.281	0.698
Low EP	6.450	5.017	0.693	36	5.733	0.706
High CEP	2.770	2.576	0.878	22	4.029	0.690
Low CEP	6.492	5.846	0.682	30	6.925	0.734
High DP	3.059	2.957	0.898	22	4.449	0.708
Low DP	5.691	4.082	0.737	34	5.356	0.711
Zero DP	11.222	10.956	0.557	40	8.978	0.763

Panel C: French portfolios between 1975:01 and 2010:12.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
MKT	4.552	5.184	0.723	31	4.993	0.735
High BM	4.809	6.290	0.748	31	5.275	0.713
Low BM	4.943	5.001	0.730	31	5.422	0.748
High EP	5.240	6.796	0.745	31	5.747	0.738
Low EP	5.391	4.608	0.713	29	6.321	0.733
High CEP	4.682	5.734	0.772	33	4.824	0.699
Low CEP	4.794	5.027	0.767	25	6.520	0.735
High DP	3.631	4.374	0.811	25	4.938	0.721
Low DP	6.012	6.632	0.676	31	6.594	0.752
Zero DP	6.781	6.723	0.662	25	9.223	0.708

Table 9 Continued.

Panel D: German portfolios between 1975:01 and 2010:12.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
MKT	4.272	5.191	0.755	32	4.539	0.723
High BM	3.426	4.973	0.804	28	4.160	0.713
Low BM	5.872	6.532	0.706	29	6.884	0.699
High EP	3.914	6.543	0.738	22	6.048	0.730
Low EP	5.456	5.889	0.723	33	5.622	0.699
High CEP	3.377	4.242	0.831	34	3.377	0.696
Low CEP	5.410	6.327	0.689	25	7.357	0.725
High DP	3.045	4.885	0.811	26	3.982	0.733
Low DP	5.262	6.896	0.718	31	5.771	0.699
Zero DP	11.785	10.579	0.566	28	14.311	0.750

Panel E: Italian portfolios between 1975:01 and 2010:12.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
MKT	6.373	4.863	0.662	29	7.471	0.716
High BM	7.849	6.499	0.623	36	7.413	0.706
Low BM	6.214	4.560	0.667	31	6.815	0.701
High EP	4.391	5.077	0.694	33	4.524	0.718
Low EP	7.273	5.099	0.618	32	7.727	0.713
High CEP	5.776	4.714	0.716	32	6.137	0.684
Low CEP	7.413	5.599	0.593	21	12.002	0.745
High DP	4.266	5.180	0.706	29	5.002	0.708
Low DP	8.315	5.636	0.593	41	6.895	0.730
Zero DP	9.773	8.406	0.588	29	11.458	0.738

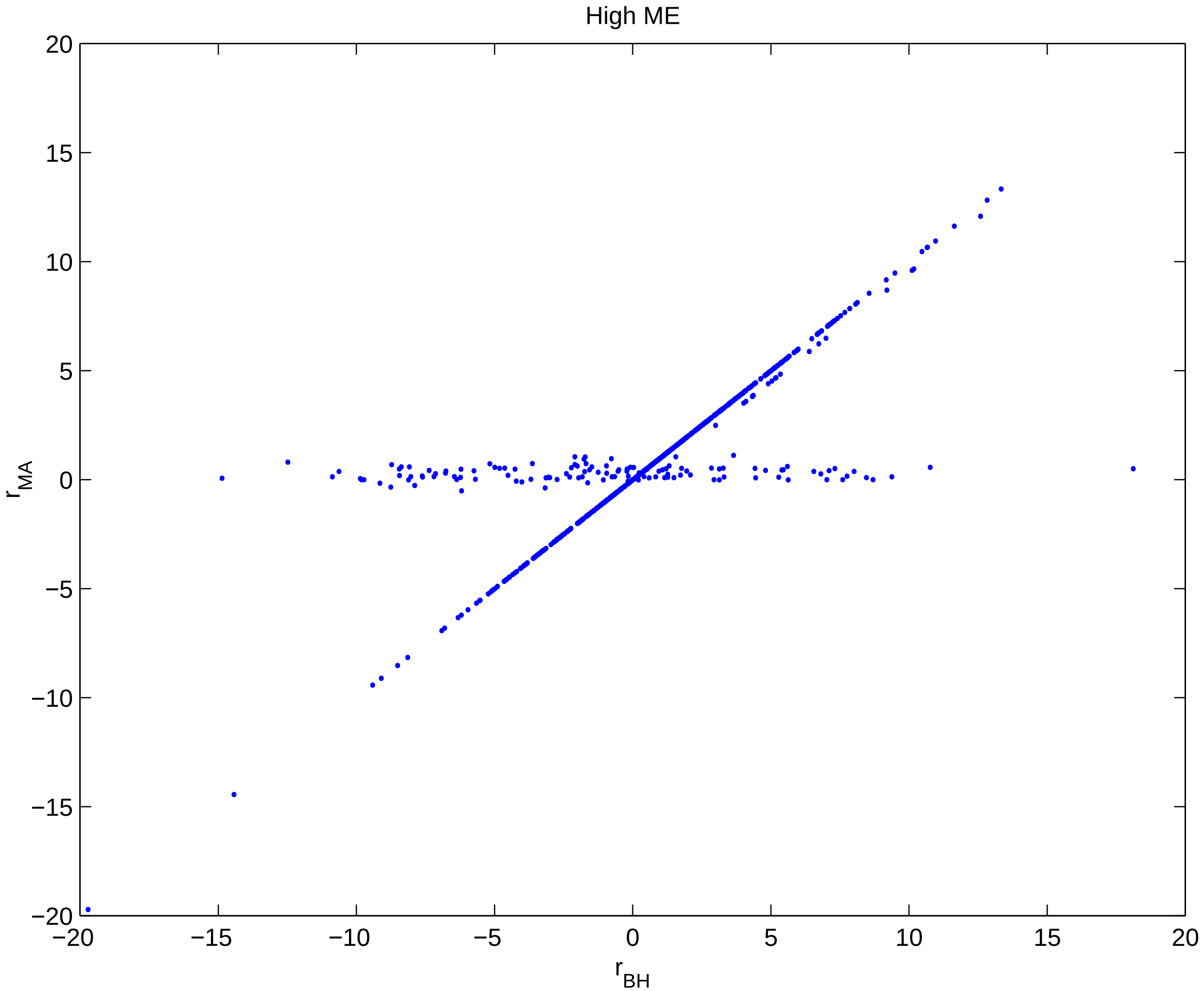
Panel F: Japanese portfolios between 1975:01 and 2010:12.

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
MKT	6.792	6.082	0.642	22	10.496	0.745
High BM	5.314	5.705	0.735	24	7.529	0.728
Low BM	9.756	7.033	0.583	32	10.366	0.735
High EP	4.792	4.853	0.730	20	8.146	0.691
Low EP	9.004	7.647	0.608	26	11.775	0.723
High CEP	4.307	4.073	0.730	16	9.152	0.696
Low CEP	8.933	7.524	0.561	32	9.491	0.755
High DP	5.743	4.843	0.703	22	8.876	0.708
Low DP	9.647	6.979	0.576	34	9.647	0.735
Zero DP	9.601	9.626	0.593	28	11.659	0.733

Panel G: UK portfolios between 1975:01 and 2010:12.

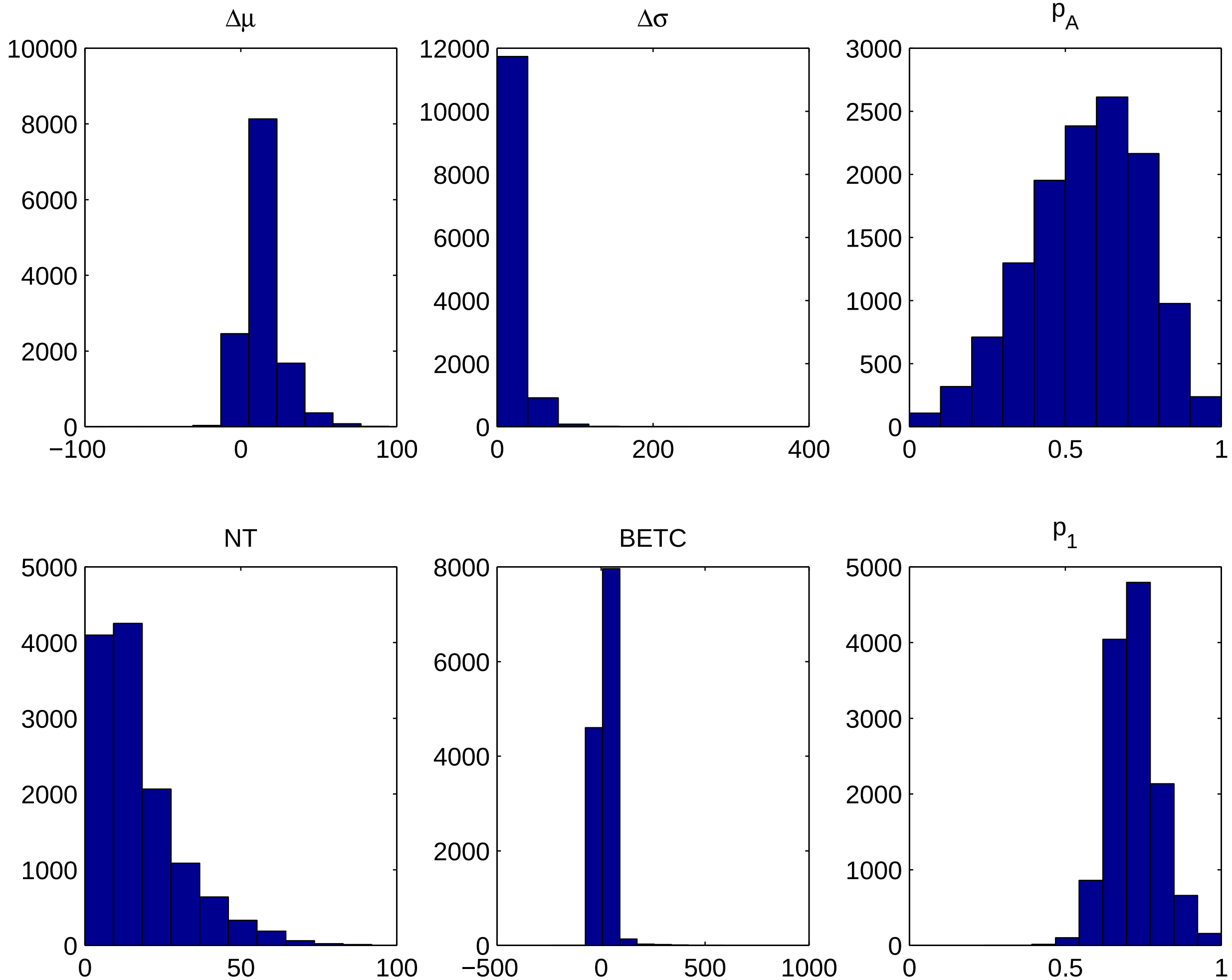
Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1
MKT	2.277	2.030	0.860	20	3.871	0.713
High BM	3.406	3.723	0.860	16	7.237	0.696
Low BM	3.200	2.684	0.811	22	4.945	0.716
High EP	3.653	2.866	0.890	24	5.175	0.672
Low EP	3.866	2.937	0.828	20	6.571	0.725
High CEP	2.750	2.701	0.902	20	4.675	0.676
Low CEP	3.432	2.785	0.809	14	8.335	0.735
High DP	2.773	3.760	0.877	26	3.626	0.679
Low DP	3.495	3.370	0.821	14	8.487	0.716

Figure 1. Scatter Plot of Buy-and-Hold returns versus the Moving Average returns: High ME decile portfolio



Notes: Figure 1 presents a scatter plot of the returns of the High ME decile buy-and-hold portfolio returns versus the moving average strategy returns. The sample contains 624 monthly observations and the data covers the 1960:01 until 2011:12 period.

Figure 2. Performance of MA strategy with individual stocks



Notes: Figure 2 presents histograms of the annualized percentage change improvement of MA over BH ($\Delta\mu$), the annualized percentage change improvement in standard deviation of return ($\Delta\sigma$), the percentage active (p_A), the number of trades (NT), break-even transaction cost (BETC) and the percentage of times the MA return exceeds the risk-free rate (p_1) for the entire sample of stock in the CRSP database for which there is at least 48 contiguous non-missing monthly returns available during the 1960:01 until 2011:12 period.