A New Anomaly: The Cross-Sectional Profitability of Technical Analysis

Yufeng Han
University of Colorado Denver
Ke Yang
RGA Reinsurance Company
and
Guofu Zhou
Washington University in St. Louis*

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Correspondence: Guofu Zhou, Olin School of Business, Washington University, St. Louis, MO 63130; e-mail: zhou@wustl.edu, phone: 314-935-6384.

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Abstract

In this paper, we document that an application of a moving average timing strategy of technical analysis to portfolios sorted by volatility generates investment timing portfolios that often outperform the buy-and-hold strategy substantially. For high volatility portfolios, the abnormal returns, relative to the CAPM and the Fama-French three-factor models, are of great economic significance, and are greater than those from the well known momentum strategy. Although both the moving average timing and momentum strategies are trend-following strategies, their performances are surprisingly uncorrelated and behave differently over the business cycles. In addition, the abnormal returns cannot be explained by market timing ability, investor sentiment, default and liquidity risks.

JEL Classification: G11, G14

Keywords: Technical Analysis, Moving Average, Anomaly, Market Timing, Conditional Model

I Introduction

Technical analysis uses past prices and perhaps other past data to predict future market movements. In practice, all major brokerage firms publish technical commentary on the market and many of their advisory services are based on technical analysis. Many top traders and investors use it partially or exclusively (see, e.g., Schwager, 1993, 1995; Covel, 2005; Lo and Hasanhodzic, 2009). Whether technical analysis is profitable or not is an issue discussed in empirical studies going as far back as Cowles (1933) who found inconclusive evidence. Recent studies, such as Brock, Lakonishok, and LeBaron (1992) and Lo, Mamaysky, and Wang (2000), however, find strong evidence of profitability when using technical analysis, primarily of using a moving average scheme, to forecast the market. More recently, Neely, Rapach, Tu and Zhou (2011) find that the stock market forecasting power of technical analysis is as good as using economic fundamentals. From a theoretical point of view, Zhu and Zhou (2009) demonstrate that technical analysis can be a valuable learning tool under uncertainty about market dynamics.

Our paper provides the first study on the cross-sectional profitability of technical analysis. Unlike existing studies that apply technical analysis to either market indices or individual stocks, we apply it to volatility decile portfolios, i.e., those portfolios of stocks that are sorted by their standard deviation of daily returns. There are three factors that motivate our examination of the volatility decile portfolios. First, we view technical analysis as one of the signals investors use to make trading decisions. When stocks are volatile, other signals, such as earnings and economic outlook, are likely to be imprecise, and hence investors tend to rely more heavily on technical signals. Therefore, if technical signals are truly profitable, this is likely to show up for high volatility stocks rather than for low volatility stocks. Second, theoretical models, such as Brown and Jennings (1989), show that rational investors can gain from forming expectations based on historical prices and this gain is an increasing function of the volatility of the asset. Third, our use of technical analysis focuses on applying the popular technical tool, the moving averages, to time investments. This is a trend-following strategy, and hence the profitability of the strategy relies on whether there are detectable trends in the cross-section of the stock market. Zhang (2006) argues that stock price continuation is due to under-reaction to public information by investors, and investors will under-react even more in case of greater information uncertainty which is well approximated by asset volatility. Therefore, to understand the cross-sectional profitability of technical analysis, it is a sensible starting point to examine the volatility decile portfolios.

We apply the moving average (MA) strategy to 10 volatility decile portfolios formed from stocks traded on the NYSE/Amex by computing the 10-day average prices of the decile portfolios.[1] For a given portfolio, the MA investment timing strategy is to buy or continue to hold the portfolio today when yesterday's price is above its 10-day MA price, and to invest the money into the risk-free asset (the 30-day Treasury bill) otherwise. Similar to the existing studies on the market, we compare the returns of the 10 MA timing portfolios with the returns on the corresponding decile portfolios under the buy-and-hold strategy. We define the differences in the two returns as returns on the MA portfolios (MAPs), which measure the performance of the MA timing strategy relative to the buy-and-hold strategy. We find that the 10 MAP returns are positive and are increasing with the volatility deciles (except one case), ranging from 8.42% per annum to 18.70% per annum. Moreover, the CAPM risk-adjusted returns, or the abnormal returns, are also increasing with the volatility deciles (except one case), ranging from 9.34% per annum to 21.95% per annum. Similarly, the Fama-French risk-adjusted returns also vary monotonically (except one case) from 9.83% per annum to 23.72% per annum.[2] In addition, the betas are either negative or negligibly small, indicating that the MAPs have little (positive) factor risk exposures.

How robust are the results? We address this question in four ways. First, we consider alternative lag lengths, of $L = 20, 50, 100$ and 200 days, for the moving averages. We find that the abnormal returns appear more short-term with decreasing magnitude over the lag lengths, but they are still highly economically significant with the long lag lengths. For example, the abnormal returns range from 7.93% to 20.78% per annum across the deciles when $L = 20$, and remain mostly over 5% per annum when $L = 200$. Second, we also apply the same MA timing strategy to the commonly used value-weighted size decile portfolios from NYSE/Amex/Nasdaq, which are a proxy of the volatility deciles. Excluding the largest size decile or the decile portfolio that is the least volatile, we obtain similar results that, when $L = 10$, the average returns of the MAPs range from 9.82% to 20.11% per annum, and the abnormal returns relative to the Fama-French model range from 13.70% to 21.87% per

[1] We obtain similar results with volatility deciles formed from stocks traded on the Nasdaq or NYSE, respectively.

[2] These major results are replicated by a conference discussant, PhD students from top universities and practitioners around the world.

annum. Third, we examine the trading behavior and break-even transaction costs. It turns out that the MA timing strategy does not trade very often and the break-even transaction costs are reasonably large. Finally, we assess the performance over subperiods and find that the major conclusions are unaltered.

The abnormal returns on the MAPs constitute a new anomaly. In his extensive analysis of many anomalies published by various studies, Schwert (2003) finds that the momentum anomaly appears to be the only one that is persistent and has survived since its publication. The momentum anomaly, published originally in the academic literature by Jegadeesh and Titman (1993), is about the empirical evidence that stocks which perform the best (worst) over a three- to 12-month period tend to continue to perform well (poorly) over the subsequent three to 12 months. Comparing the momentum with the MAPs, the momentum anomaly earns roughly about 12% annually, substantially smaller than the abnormal returns earned by the MA timing strategy on the highest volatility decile portfolio. Furthermore, interestingly, even though both the momentum and MAP anomalies are results of trend-following, they capture different aspects of the market because their return correlation is low, ranging from -0.01 to 0.07 from the lowest decile MAP to the highest decile MAP. Moreover, the MAPs generate economically and statistically significant abnormal returns (alphas) in both expansion and recession periods, and generate much higher abnormal returns in recessions. In contrast, the momentum strategy fails to generate any risk-adjusted abnormal returns during recessionary periods. In short, despite the trend-following nature of both strategies, the MAP and momentum are two distinct anomalies.[3]

To understand further the abnormal returns on the MAPs, we address two more questions. First, we analyze whether the strategy has any ability in timing the market, and whether there is still abnormal returns after controlling for this ability. We find that there is certain timing ability, but the abnormal returns remain after controlling for it. Second, we examine whether the abnormal returns can be explained by a conditional version of the Fama-French model (see, e.g., Ferson and Schadt (1996)). We find that returns on the MAPs are not sensitive to changes in investor sentiment and Pástor and Stambaugh (2003) liquidity factor, but have lower market betas in recessions and higher betas during periods with higher default risk. Nevertheless, the abnormal returns are robust, and remain statistically and economically significant.

[3]Han and Zhou (2011) explore how technical analysis can help to enhance the popular momentum strategy.

The rest of the paper is organized as follows. Section II discusses the investment timing strategy using the MA as the timing signal. Section III provides evidence for the profitability of the MA timing strategy. Section IV examines the robustness of the profitability in a number of dimensions. Section V compares the momentum strategy and the MA timing strategy over the business cycles and examines the sensitivity of the abnormal returns to economic variables. Section VI provides concluding remarks.

II The Moving Average Timing Strategies

We use one set of 10 volatility decile portfolios and one set of 10 size decile portfolios in this paper. All of the data are readily available from the Center for Research in Security Prices (CRSP). More specifically, the first set is constructed based on the NYSE/Amex stocks sorted into ten groups (deciles) by their annual standard deviations estimated using the daily returns within the year.[4] Once stocks are assigned to portfolios, portfolio index levels (prices) and daily returns are calculated via equal-weighting.[5] The portfolios are rebalanced each year at the end of the previous year. The second set is the 10 value-weighted size decile portfolios sorted by firm size with stocks traded on the NYSE/Amex/Nasdaq. Similar to the volatility deciles, the size deciles are ranked using the firm size at the end of the previous year and rebalanced each year. The sample period for both the volatility decile portfolios and the size decile portfolios is from July 1, 1963 to December 31, 2009 to coincide with the Fama-French factors.

Denote by R_{jt} $(j = 1, \ldots, 10)$ the returns on either of the two sets of decile portfolios, and by P_{jt} $(j = 1, \ldots, 10)$ the corresponding portfolio prices (index levels). The moving average (MA) at time t of lag L is defines as

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

which is the average price of the past L days. Following, for example, Brock, Lakonishok, and LeBaron (1992), we consider 10-, 20-, 50-, 100- and 200-day moving averages in this paper. The MA indicator is the most popular strategy of using technical analysis and is the

[4] In CRSP, portfolio (decile) one contains the stocks with the highest standard deviation. We follow the convention of published studies on sorted portfolios by reversing the order, so our portfolio (decile) one contains the stocks with the lowest standard deviation.

[5] CRSP does not have value-weighted volatility decile portfolios while the value-weighting is an interesting alternative, which is the reason we also analyze the value-weighted size decile portfolios below.

focus of study in the literature. On each trading day t, if the last closing price P_{jt-1} is above the MA price $A_{jt-1,L}$, we will invest in the decile portfolio j for the trading day t, otherwise we will invest in the 30-day Treasury bill. So the MA provides an investment timing signal with a lag of one day. The idea of the MA is that an investor should hold an asset when the asset price is on an uninterrupted up trend, which may be due to a host of known and unknown factors to the investor. However, when the trend is broke, new factors may come into play and the investor should then sell the asset. Its theoretical reasons and empirical evidence will be examined in the next section.

Mathematically, the returns on the MA timing strategy are

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

where R_{jt} is the return on the j-th volatility decile portfolio on day t, and r_{ft} is the return on the risk-free asset, the 30-day Treasury bill. Similar to existing studies on the performance of the market timing strategy relative to the buy-and-hold strategy of the market portfolio, we focus on the cross-sectional profitability of the MA timing strategy relative to the buy-and-hold strategy of the volatility decile portfolios. In other words, we focus on how $\tilde{R}_{jt,L}$ outperforms R_{jt}; that is, we will be interested in the difference $\tilde{R}_{jt,L} - R_{jt}$. Because the performance of this difference depends on the usefulness of the MA signal, we call the difference the return on the MA portfolio (MAP). With the 10 decile portfolios, we thus obtain 10 MAPs,

$$\text{MAP}_{jt,L} = \tilde{R}_{jt,L} - R_{jt}, \quad j = 1, \ldots, 10. \tag{3}$$

A MAP can also be interpreted as a zero-cost arbitrage portfolio that takes a long position in the MA timing portfolio and a short position in the underlying volatility decile portfolio. The abnormal performance of the MAPs indicate the profitability of the MA investment timing strategy.

III Profitability of the Moving Average Portfolios

In this section, we provide first the summary statistics of the volatility decile portfolios, the 10-day MA timing portfolios, and the corresponding MAPs, and then the alphas (abnormal returns) of the MAPs, which reveal strong evidence of the cross-sectional profitability of the MA timing strategy. Finally, we explore some explanations for the profitability.

A Summary Statistics

Table I reports the basic characteristics of the returns on the decile portfolios, R_{jt}, the returns on the 10-day MA timing portfolios, $\tilde{R}_{jt,10}$, and the returns on the corresponding MAPs, $\mathrm{MAP}_{jt,10}$. Panel A provides the average return, the standard deviation, the skewness, and the Sharpe ratio of the buy-and-hold strategy across the ten volatility deciles. The returns are an increasing function of the deciles, ranging from 10.81% per annum for the lowest decile to 44.78% per annum for the highest decile.[6] The last row in the table provides the difference between the highest and the lowest deciles. Similarly, the MA timing portfolios, reported in Panel B, also have returns varying positively with the deciles, ranging from 19.22% to 60.51% per annum.[7] In addition, the returns on the MA timing portfolios not only are larger than those on the decile portfolios, but also enjoy substantially smaller standard deviations. For example, the standard deviation is 4.16% versus 6.82% for the lowest decile, and 14.41% versus 20.29% for the highest decile. In general, the MA timing strategy yields only about 65% volatility of the decile portfolios. As a result, the Sharpe ratios are much higher for the MA timing portfolios than for the volatility decile portfolios, about four times higher in general. Furthermore, while the volatility decile portfolios display negative skewness (except for the highest volatility decile), the MA timing strategy yields either much smaller negative skewness or positive skewness across the volatility deciles. Panel C reports the results for the MAPs. The returns increase monotonically from 8.42% to 18.70% per annum across the deciles (except for the highest volatility decile). While the standard deviations are much smaller than those of R_{jt} in the corresponding deciles, they are not much different from those of $\tilde{R}_{jt,L}$. However, the skewness of the MAPs across all deciles is positive and large. In the last column of Panel C, we report the success rate of the MA timing strategy, which is defined as the fraction of trading days when the MA timing strategy is on the "right"

[6] Ang, Hodrick, Xing, and Zhang (2006) document a negative relation between lagged idiosyncratic volatility and future returns, while Han and Lesmond (2011) argue that the negative relation is due to liquidity bias in the estimation of idiosyncratic volatility, and Huang, Liu, Rhee, and Zhang (2009) argue that the negative relation is due to return reversal. However, positive contemporaneous relation between stock returns and volatilities (on both the aggregate market and individual stock level) has been supported by both theory (e.g. Merton, 1973, 1987; Malkiel and Xu, 2004) and empirical evidence (e.g. Lehmann, 1990; Malkiel and Xu, 2004; Spiegel and Wang, 2005; Ghysels, Santa-Clara, and Valkanov, 2005; Fu, 2009).

[7] To put the performance of the volatility decile portfolios and MA timing portfolios in perspective, the equal-weighted NYSE/Amex index has an average return of 17.45% per annum, and a standard deviation of 13.53% per annum in the same period. Therefore, even the lowest decile of the MA timing portfolios earns higher returns than the equal-weighted index, while the returns of the lowest four volatility deciles are lower than those of the index. The standard deviation of all the MA timing portfolios is also smaller than that of the index except for the highest decile.

side of the market, i.e., it is out of the market when the decile returns are lower than the risk-free rate; it is in the market when the decile returns are higher than the risk-free rate. The success rate is about 60% across the deciles, indicating good timing performance of the MA timing strategy.

The simple summary statistics clearly show that the MA timing strategy performs well. The MA timing portfolios outperform decile portfolios with higher Sharpe ratios by having higher average returns and lower standard deviations. Furthermore, the MA timing portfolios have either less negative or positive skewness, and in particular the MAPs all have large positive skewness and above 50% success rates, which suggests that more often than not the MA timing strategy generates large positive returns. However, it is unclear whether the extra returns can be explained by a risk-based model. This motivates our next topic of examining their portfolio return differences, the MAPs, in the context of factor models.

B Alpha

Consider first the capital asset pricing model (CAPM) regression of the zero-cost portfolio returns on the market portfolio,

$$\text{MAP}_{jt,L} = \alpha_j + \beta_{j,mkt} r_{mkt,t} + \epsilon_{jt}, \quad j = 1, \ldots, 10, \tag{4}$$

where $r_{mkt,t}$ is the daily excess return on the market portfolio. Panel A of Table II reports the results of the daily CAPM regressions of the MAPs formed with 10-day MA timing strategy.[8] The alphas or risk-adjusted returns are even greater than the unadjusted ones, ranging from 9.31% to 21.76% per annum. The alphas also increase monotonically from the lowest volatility decile to higher volatility deciles,[9] except that the highest decile yields a slightly lower alpha than the ninth decile. Nevertheless, the highest volatility decile still generates an alpha that is about twice (18.32/9.31) as large as that generated by the lowest decile. The difference is reported in the last row, which is substantial and highly significant.

[8] To utilize more sample information, we use daily regressions in this paper. However, monthly regression results are similar. For example, the CAPM alphas will be 9.77%, 10.37%, 10.81%, 12.25%, 14.15%, 15.59%, 16.64%, 20.80%, 22.93% and 19.26% with monthly regressions. They are very close and slightly higher than those reported in Table II. We also include lagged market factors in the daily regression to deal with stale prices and obtain virtually the same results.

[9] For brevity, we do not report similar results based on other CRSP volatility decile portfolios. For example, the CRSP has the same volatility decile portfolios based on NASDAQ stocks, and the associated alphas have the same pattern and range from 6.17% to 23.93% per annum.

The large risk-adjusted abnormal returns clearly demonstrate the profitability of the MA timing strategy. The fact that the alphas are higher than the average returns is because the MAPs have negative market betas. As shown in Panel A of Table II, the market betas for the MAPs range from -0.61 to -0.18. The intuition can be understood as follows. The MA timing strategy is designed to avoid the negative portfolio returns. When the portfolio returns are negative, the market is most likely down too; because of their successful timing ability, however, the MA timing portfolios have much better returns than the underlying volatility decile portfolios. When the portfolio returns are positive, the market is most likely up as well; since the MA indicators tend to be more cautious in that they turn positive only after some time, the MA timing portfolios may have smaller returns than the underlying volatility decile portfolios. As a result, the market betas of the MA timing portfolios are smaller than those of the underlying volatility decile portfolios, and hence the market betas of the MAPs are negative.

Consider further the alphas based on the Fama and French (1993) three-factor model,

$$\mathrm{MAP}_{jt,L} = \alpha_j + \beta_{j,mkt} r_{mkt,t} + \beta_{j,smb} r_{smb,t} + \beta_{j,hml} r_{hml,t} + \epsilon_{jt}, \quad j = 1, \ldots, 10, \tag{5}$$

where $r_{mkt,t}$, $r_{smb,t}$, and $r_{hml,t}$ are the daily market excess return, daily return on the SMB factor, and daily return on the HML factor, respectively. Panel B of Table II reports the results. The alphas are even greater than before, sharing the same general pattern of increasing values with the deciles. The market betas become slightly more negative than those in the CAPM case. Interestingly, all the betas on both the SMB and HML factors are negative too. This is again due to less exposure of the MA timing strategy to these factors. But the magnitude of the betas are smaller than those on the market factor. The results seem to suggest that MAPs are excellent portfolios for investors to hold for hedging risks of the market portfolio and the SMB and HML factors. On model fitting, similar to other studies, the three-factor model does have better explanatory power than the CAPM, evidenced by higher adjusted R^2s, and the improvement increases with the deciles.[10]

[10] Table I and II are the major results of this paper, which show the surprisingly good performance of the MAPs. These results are not only verified by our careful studies, but also supported by our confirmations received from people in both academia and industry.

C Explanations

The large alphas provided in the previous subsection clearly indicate the profitability of using technical analysis, particularly the MA timing strategy. The question is why it can be profitable in the competitive financial markets. This lies in the predictability of the market.

In earlier studies of stock price movements in the 70s, a random walk model and similar ones are commonly used, in which stock returns are assumed to be unpredictable. In this case, the profitability of using technical analysis and the existence of any anomaly, are ruled out by design. However, later studies, such as Fama and Schwert (1977) and Campbell (1987), find that various economic variables can forecast stock returns. Recent studies, such as Ferson and Harvey (1991), Ang and Bekaert (2007), Campbell and Thompson (2008), Cochrane (2008), Rapach, Strauss, and Zhou (2010) provide further evidence on return predictability. Many recent theoretical models allow for predictability as well (see, e.g., Cochrane, 2008, and the references therein). The predictability of stock returns permits the possibility of profitable technical rules.

Indeed, Brock, Lakonishok, and LeBaron (1992) provide strong evidence on the profitability of using the MA signal to predict the Dow Jones Index, and Lo, Mamaysky, and Wang (2000) further find that technical analysis adds value to investing in individual stocks beyond the index. Neely, Rapach, Tu, and Zhou (2010) provide the most recent evidence on the value of technical analysis in forecasting market risk premium. Covering over 24,000 stocks spanning 22 years, Wilcox and Crittenden (2009) continue to find profitability of technical analysis. Across various asset classes, Faber (2007) shows that technical analysis improves the risk-adjusted returns. In other markets, such as the foreign exchange markets, evidence on the profitability of technical analysis is even stronger. For example, LeBaron (1999) and Neely (2002), among others, show that there are substantial gains with the use of the MA signal and the gains are much larger than those for stock indices. Moreover, Gehrig and Menkhoff (2006) argue that technical analysis is as important as fundamental analysis to currency traders.

From a theoretical point of view, incomplete information on the fundamentals is a key for investors to use technical analysis. In such a case, for example, Brown and Jennings (1989) show that rational investors can gain from forming expectations based on historical prices, and Blume, Easley, and O'Hara (1994) show that traders who use information contained in market statistics do better than traders who do not. With incomplete information, the investors can face model uncertainty even if the stock returns are predictable. In this case, Zhu and Zhou (2009) show that MA strategies can help to learn about the predictability and thus can add value to asset allocation. Note that both the MA and momentum strategies are trend-following. The longer a trend continues, the more profitable the strategies may become. Hence, models that explain momentum profits can also help to understand the profitability of the MA indicators. In the market under-reaction theory, for example, Barberis, Shleifer, and Vishny (1998) argue that prices can trend slowly when investors underweight new information in making decisions. Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999) show that behavior biases can also lead to price continuation. Moreover, Zhang (2006) argues that stock price continuation is due to under-reaction to public information by investors.

Explanations above help to understand why the MA strategy is profitable; the question remains whether such profitability can be explained by compensation for risk. While this may well be the case, the alphas we find for the MA strategies are large. Similar to the momentum returns (see, e.g., Schwert, 2003; Jegadeesh and Titman, 1993, 2001), such magnitude of abnormal returns is unlikely explained away by a more sophisticated and known asset pricing model. Hence, we leave the search for new models in explaining the MAP anomaly to future research.

IV Robustness

In this section, we examine the robustness of the profitability of the MAPs in several dimensions. We first consider alternative lag lengths for the MA indicator, and then consider the use of the value-weighted size decile portfolios. We analyze further the trading behavior of the MA timing strategy and estimate the break-even transaction cost. Finally we examine the profitability in two subperiods.

A Alternative Lag Lengths

Consider now the profitability of the MAPs by using 20-day, 50-day, 100-day, and 200-day moving averages. Table III reports both the average returns and Fama-French alphas for the

MAPs of the various lag lengths. The results are fundamentally the same as before, but two interesting features emerge. First, the MA timing strategy still generates highly significant abnormal returns relative to the buy-and-hold strategy regardless of the lag length used to calculate the moving average price. This is reflected by the significantly positive returns and significantly positive alphas of the MAPs. For example, even when the timing strategy is based on the 200-day MA, the risk-adjusted abnormal returns range from 3.10% to 8.04% per annum and are all significant. However, the magnitude of the abnormal returns does decrease as the lag length increases. The decline is more apparent for the higher ranked volatility decile portfolios, and accelerates after $L = 20$. For example, consider the case for the highest decile portfolio. The Fama-French alpha with the 20-day MA is 18.18% per annum, which is about 90% of the 10-day MA alpha (20.21% per annum reported in Table II). In contrast, the 50-day MA timing strategy generates a risk-adjusted abnormal return of 12.94%, which is about 64% of the 10-day MA alpha. In addition, the 200-day MA timing strategy only generates 5.76%, only about 29% of the risk-adjusted abnormal return of the 10-day MA.[11]

Second, similar to the 10-day MA timing strategy, all the other MA timing strategies generate monotonically increasing abnormal returns across the deciles, except for the highest decile case where it has slightly lower values than those of the ninth decile. However, differences in the abnormal returns between the highest and lowest deciles decline as the lag length increases. For example, as reported in the last row of the table, the difference is 10.25% and highly significant when $L = 20$, but is only 2.66% and insignificant when $L = 200$.

Finally, the last panel in Table III provides the performance of a random switching strategy as a reference for the performance of the MA timing. In sharp contrast with MA timing strategy, the random switching strategy yields significantly negative average returns and Fama-French alphas.[12] Furthermore, both returns decrease monotonically across the deciles with the highest volatility decile yielding an average return as low as -19.72% per annum.

[11]The monotonic relation between the lag length and the profitability in the table is apparent. However, results not reported show that shorter moving average lag lengths, for example 3-day or 5-day, do not generate higher performance than the 10-day lag length.

[12]The performance reported is the average of 10,000 random switching portfolios.

B Size Decile Portfolios

CRSP volatility decile portfolios are equal-weighted, which raises a concern about the larger role the small stocks play in these portfolios than they play in the value-weighted case. To mitigate this concern, we use the value-weighted size portfolios to further check the robustness of the results. Since smaller size deciles have larger volatilities, the 10 size portfolios may be viewed approximately as another set of volatility decile portfolios.

Table IV reports the average returns and Fama-French alphas for the MAPs based on the size portfolios formed with value-weighting based on stocks traded on NYSE/Amex/Nasdaq.[13] With the important exception on the largest size portfolio which tends to have the least volatile stocks, the results are similar to the previous ones using the volatility decile portfolios. Across all the lag lengths, the alphas on the MAPs based on the largest size portfolio are about only 3% per annum. Nevertheless, starting from the next largest decile (the 2nd decile), both the average returns and Fama-French alphas increase from large stock deciles to small stock deciles, and the magnitude is comparable to that of the volatility decile portfolios. For example, the Fama-French alphas range from 13.70% to 22.37% when $L = 10$. The last row provides the differences between the smallest and the largest deciles, which are both economically and statistically significant for all cases except the 200-day MA. Overall, it is clear that the profitability of the MA timing strategy remains strong with the use of the value-weighted size decile portfolios.

Small size effect was first documented by Banz (1981) and Reinganum (1981) who show that small stocks traded on NYSE earn higher average returns than is predicted by the CAPM. Many subsequent studies confirm the small size effect. Fama and French (1993) use the small size effect to form the SMB factor. However, Schwert (2003) show that the small size effect has disappeared after its initial publication.

Table V reports the results of the CAPM regressions of the size decile portfolios, and the corresponding MAPs in the period from January 02, 2004 to December 31, 2009. All the alphas of the size decile portfolios are insignificant in this subperiod, even for the smallest size decile, consistent with Schwert (2003). In contrast, the MAPs based on the size portfolios still have significantly positive alphas from decile seven to decile 10. In addition, the abnormal returns are as large as before in magnitude, and are of great economic significance. For

[13] Similar results are obtained if the size decile portfolios are formed by using only NYSE stocks.

example, the MAP for the smallest decile yield an annualized abnormal return of 21.10%. It is interesting that while the size anomaly disappears in this subperiod, the MA anomaly is alive and well. This suggests that trading the size portfolios can still earn abnormal profits with the use of technical analysis.

C Average Holding Days, Trading Frequency and Break-Even Transaction Costs

Since the MA timing strategy is based on daily signals, it is of interest to see how often it trades. If the trades occur too often, it will be of real concern whether the abnormal returns can survive transaction costs. We address this issue by analyzing the average holding days of the timing portfolios, their trading frequency, as well as their break-even trading costs, upon which the average returns of the MAPs become zero.

The average holding days are reported in Table VI. It is not surprising that longer lag lengths result in longer average holding days as longer lag lengths capture longer trends. For example, the 10-day MA timing strategy has about 9 to 10 holding days on average, whereas the 200-day MA timing strategy has average holding days ranging from 60 to 83 days. In addition, the differences in the holding days across the deciles also increase with the lag length. The lowest volatility deciles often has the longest holding days, whereas the highest volatility decile often has the shortest holding days. To assess further on trading, we also estimate the fraction of days when the trades occur relative to the total number of days and report it as 'Trading Frequency (Trading)' in Table VI. Since longer lag lengths have longer average holding days, the trading frequency is inversely related to the lag length. For example, the 10-day MA strategy requires about 20% trading days, whereas the 200-day MA has about only 3%, a very small number.

Consider now how the abnormal returns will be affected once we impose transaction costs on all the trades. Intuitively, due to the large size of the abnormal returns, and due to the modest amount of trading, the abnormal returns are likely to survive.

Following Balduzzi and Lynch (1999), Lynch and Balduzzi (2000), and Han (2006), for example, we assume that we incur transaction costs for trading the decile portfolios but no costs for trading the 30-day Treasury Bill. Then, in the presence of transaction cost τ per trade, the returns on the MA timing strategy are:

$$\tilde{R}_{jt,L} = \begin{cases} R_{jt}, & \text{if} \quad P_{jt-1} > A_{jt-1,L} \quad \text{and} \quad P_{jt-2} > A_{jt-2,L}; \\ R_{jt} - \tau, & \text{if} \quad P_{jt-1} > A_{jt-1,L} \quad \text{and} \quad P_{jt-2} < A_{jt-2,L}; \\ r_{ft}, & \text{if} \quad P_{jt-1} < A_{jt-1,L} \quad \text{and} \quad P_{jt-2} < A_{jt-2,L}; \\ r_{ft} - \tau, & \text{if} \quad P_{jt-1} < A_{jt-1,L} \quad \text{and} \quad P_{jt-2} > A_{jt-2,L}. \end{cases} \tag{6}$$

Determining the appropriate transaction cost level is always a difficult issue, and recent studies use a transaction cost level ranging from one basis point to 50 basis points. For example, Balduzzi and Lynch (1999) use one basis point and 50 basis points as the lower and upper bounds for transaction costs, and Lynch and Balduzzi (2000) consider a transaction cost of 25 basis points.[14] Without taking a stand on the magnitude of the appropriate transaction costs, we consider the break-even transaction costs that make the average return of the MAPs zero. Table VI reports the break-even transaction costs (BETC) in basis points. Generally the break-even transaction costs decrease across the volatility decile, with the lowest deciles have the highest break-even transaction costs, which is consistent with the patterns of the average holding days and trading frequencies. Across different MA lag lengthes, MA(50) has the highest break-even transaction costs, as high as 111.52 bps, while MA(10) has the lowest break-even transaction costs. The lowest break-even cost is with MA(10) decile eight, about 28.80 bps. Overall, the break-even transaction costs are reasonably high, which suggest that the MAPs should still earn economically highly significant abnormal returns after considering appropriate transaction costs.[15]

D Subperiods

Now we further check the robustness of the profitability of the MA timing strategy by examining its performance over subperiods. To avoid possible bias in affecting the performance, we simply divide the entire sample period into two subperiods with roughly equal time length.

Table VII reports the abnormal returns and beta coefficients from both the CAPM and the Fama-French models. In both subperiods, the MAPs yield significant and positive ab-

[14]Although not reported in the tables, at the cost of 25 basis points per trade, the 20-day MA experiences only about 3 to 4% per annum drop in abnormal performance, whereas the 200-day MA has only about 0.7 to 1.0% drop in the abnormal returns. Nevertheless, for the high volatility deciles, all the MAPs still have significantly positive abnormal returns.

[15]The debate on the correct amount of transaction costs is unlikely to get resolved in our exploratory study here, but will be an interesting topic of future research. To see the difficulty, this issue for the momentum strategy is not really settled after hundreds of studies since the seminal work of Jegadeesh and Titman (1993) who do not examine this issue in their paper.

normal returns, similar to the case of the entire sample period. Moreover, both the CAPM and the Fama-French alphas increase monotonically across the deciles except for the highest decile which often has lower alphas than the ninth decile. Once again, the market betas are significantly negative, so are the SMB betas. In addition, the HML betas are largely insignificant and small in the first subperiod, but are significant and negative in the second subperiod.

However, both the CAPM and the Fama-French alphas are higher in the first subperiod than in the second subperiod, and also higher than those from the entire sample period. For example, the lowest volatility decile has a CAPM and Fama-French alpha of about 11.27% and 12.72 % per annum, respectively, in the first subperiod, but the abnormal returns reduce to 7.39% and 7.69% per annum, respectively, in the second subperiod, and are compared to 9.34% and 9.83% per annum, respectively, in the entire sample period.[16] Overall, the results continue to support that the MAPs, especially those high decile ones, constitute a new anomaly in asset pricing.

V Source of the Abnormal Returns

In this section, we further analyze the source of the superior performance of the MAPs. We first examine whether there is any market timing ability of the MA strategy, and whether this ability can explain the abnormal returns. We then compare the MA timing strategy with the momentum strategy as both are trend-following strategies. Finally we examine whether exposures to other macroeconomic variables can explain the abnormal returns of the MAPs.

A Market Timing

In addressing the market timing issue, we employ two of the popular approaches. The first is the quadratic regression of Treynor and Mazuy (1966):

$$\mathrm{MAP}_{jt,L} = \alpha_j + \beta_{j,mkt} r_{mkt,t} + \beta_{j,mkt^2} r_{mkt,t}^2 + \epsilon_{jt}, \qquad j = 1, \ldots, 10, \tag{7}$$

[16]The results in the table seem to suggest that the performance of the MAPs decreases over time. However, results for the most recent period from January 2, 2004 to December 31, 2009, although not reported, generate higher performance than the second subperiod reported in this table.

where the significantly positive coefficient, β_{j,mkt^2}, of the squared market excess return, $r^2_{mkt,t}$, indicates successful market timing. The second approach is the regression of Henriksson and Merton (1981):

$$\text{MAP}_{jt,L} = \alpha_j + \beta_{j,mkt} r_{mkt,t} + \gamma_{j,mkt} r_{mkt,t} I_{r_{mkt}>0} + \epsilon_{jt}, \qquad j = 1, \ldots, 10, \tag{8}$$

where $I_{r_{mkt}>0}$ is the indicator function taking the value of one when the market excess return is above zero, otherwise taking the value of zero. The significantly positive coefficient, γ_{mkt}, indicates successful market timing.

Table VIII provide the evidence of successful market timing for the MA timing strategy. Panel A reports the coefficients of the quadratic regression of the MAPs, and Panel B reports the coefficients of the option-like regression of the MAPs. In both regressions, the market timing coefficients, βmkt^2 and γ_{mkt}, are significantly positive, indicating successful market timing by the moving average timing strategy. However, market timing alone does not explain the abnormal returns of the MAPs. For example, in the quadratic regressions, the alphas are still significantly positive and economically large from the lowest to the highest volatility deciles. In the option-like second regression, alphas of the higher volatility deciles are still positive and significant, even though alphas of the lower deciles become insignificant.

B Comparison with Momentum

B.1 Momentum Betas

In this subsection, we examine whether momentum can explain the abnormal returns of the MAPs and compare the MAPs with the momentum factor, both of which are trend-following and zero-cost spread portfolios, by examining their performance over business cycles.

With returns on the momentum factor (UMD) which is readily available from French's web site, we first compute the correlations between UMD and the MAPs, which range from -0.01 to 0.07 from the lowest volatility decile MAP to the highest volatility decile MAP. The low correlation suggests that the MAPs may not be sensitive to the momentum factor in the following regression model:

$$\text{MAP}_{jt,L} = \alpha_j + \beta_{j,mkt} r_{mkt,t} + \beta_{j,smb} r_{smb,t} + \beta_{j,hml} r_{hml,t} + \beta_{j,umd} r_{umd,t} + \epsilon_{jt}, \quad j = 1, \ldots, 10, \tag{9}$$

where $r_{mkt,t}$, $r_{smb,t}$, r_{hml}, and $r_{umd,t}$ are the daily market excess return, daily return on the SMB factor, daily return on the HML factor, and daily return on the UMD (momentum) factor, respectively.

Table IX reports the regression results of the MAPs on the Fama-French three factors and the momentum factor. Clearly, momentum does not explain the abnormal returns of the MAPs. Similar to the CAPM model and Fama-French three-factor model, the alphas are still significantly positive and monotonically increasing across the deciles except the highest decile for which the alpha is slightly reduced. Moreover, the four-factor alphas are even slightly larger than those of the CAPM and Fama-French models. This is due to the negative exposure of the MAPs to the momentum factor.

Contrary to what is suggested by the low correlations, the momentum betas of the MAPs are statistically significant, which suggests that there is some statistical relation between the MAPs and the UMD, even though the magnitude is small. This is not surprising since both are trend-following strategies. Moreover, the additional explanatory power of the momentum factor is quite small. The last column of Table IX reports the differences of the adjusted R^2s between the four-factor regression and the Fama-French three-factor regression (Table II). The incremental R^2s are all less than 1%. Therefore, we conclude that the MAPs and the UMD are substantially different trend-following strategies. The question is whether there is any economic linkage between them, which we address below.

B.2 Business Cycles

Chordia and Shivakumar (2002) provide evidence that the profitability of momentum strategies is related to business cycles. They show that momentum payoffs are reliably positive and significant over expansionary periods, whereas they become negative and insignificant over recessionary periods. However, Griffin, Ji, and Martin (2003) find that momentum is still profitable over negative GDP growth periods and explain that the earlier finding of Chordia and Shivakumar (2002) may be due to not skipping a month between ranking and investment periods and the NBER classification of economic states. Using a new hand-collected data set of the London Stock Exchange from the Victorian era (1866–1907), thus obviating any data mining concern, Chabot, Ghysels, and Jagannathan (2010) do not find a link between momentum profits and GDP growth, either. Therefore, the overall evidence that the profitability of the momentum strategy is affected by the business cycles seems mixed. On the other hand, Cooper, Jr., Hameed, and Gutierrez Jr. (2004) argue that the momentum strategy is profitable only after an up market, where the up market is defined as having positive returns in the past one, two, or three years. Huang (2006) finds similar evidence in the international markets, and Chabot, Ghysels, and Jagannathan (2010) extend the results to the early periods of the Victorian era.

In our comparison of the performance of both the UMD and the MAPs, we regress both the UMD factor and MAPs, respectively, on the Fama-French three factors and either a *Recession* dummy variable indicating the NBER specified recessionary periods, or an *Up Market* dummy variable indicating the periods when the market return of the previous year is positive. Table X reports the results. Consistent with Griffin, Ji, and Martin (2003) and Chabot, Ghysels, and Jagannathan (2010), the *Recession* dummy variable (Panel A) is negative but insignificant for the UMD factor, suggesting that the momentum strategy is profitable in both expansionary and recessionary periods, but the profits may be smaller in recessions. In contrast, all the MAPs have significant coefficients for the *Recession* dummy. Furthermore, the coefficients are all positive, indicating that the MA timing strategy generates higher abnormal profits in recessionary periods than in expansionary periods. Nevertheless, the MAPs yield both economically and statistically significant risk-adjusted abnormal returns (alphas) in both periods, with positive alphas ranging from 8.05% to 20.72% per annum in expansionary periods and ranging from 18.75% to 37.91% per annum in recessionary periods. Because of the exceptionally high abnormal returns generated by the MAPs during recessions, one may suspect that the overall performance of the MAPs should be much higher than that in the expansion periods. Table II clearly states that this is not the case. The reason is that there are only a few recessionary periods over the entire sample period. Overall, we find that the MAPs are more sensitive to recessions and more profitable in recessions than the UMD. From an asset pricing perspective, this is valuable. In the case of negative returns on the market (shortage of an asset), the positive returns are worth more than usual (the price of the asset will be higher than normal).

Panel B of Table X reports the results with the *Up Market* dummy variable. Consistent with Cooper, Jr., Hameed, and Gutierrez Jr. (2004), Huang (2006), and Chabot, Ghysels, and Jagannathan (2010), the alpha of the UMD factor is insignificant, indicating that the momentum strategy has insignificant risk-adjusted abnormal returns following the down market, whereas the coefficient of the *Up Market* dummy is statistically significant and economically considerable, about 10.86% per annum. In contrast, the coefficients of the *Up Market* dummy are negative for all the MAPs, and about half of them are statistically significant. This is probably due to mean-reversion in the price that cannot be immediately captured by the MA timing strategy. Nevertheless, the abnormal returns of the MAPs are still highly significant and positive following the up market. On the other hand, the abnormal returns of the MAPs are much higher following the down market, a result that is very different from that of the momentum factor, but similar to that of MAPs using the NBER recession dummy variable in Panel A.

C Conditional Models with Macroeconomic Variables

Ferson and Schadt (1996) advocate to use conditional asset pricing models to evaluate portfolio performance because alphas from the unconditional model will be biased if expected returns and risks associated with the market and other factors change over time. Therefore, we utilized the conditional version of the Fama-French three-factor model to measure the abnormal returns of the MAPs.

The conditional model is specified as

$$\mathrm{MAP}_{jt,L} = \alpha_j + \beta_{j,mkt} r_{mkt,t} + \beta_{j,smb} r_{smb,t} + \beta_{j,hml} r_{hml,t} + \beta_{j,Z} Z_{t-1} + \gamma_{j,S} Z_{t-1} r_{mkt,t} + \epsilon_{jt},$$
$$j = 1, \ldots, 10, \tag{10}$$

where Z represents the conditional variables that could affect the expected returns and/or risks. In this subsection, we use investor sentiment (Baker and Wurgler, 2006), default spread, and liquidity (Pástor and Stambaugh, 2003) as the conditional variables as stock volatilities are closely related to these variables.

Baker and Wurgler (2006, 2007) provide evidence that investor sentiment is related to expected returns and risks of the market. Baker and Wurgler (2006) also argue that volatility is linked to investor sentiment. When investor sentiment is low, high volatility stocks tend to yield high future returns; when investor sentiment is high, high volatility stocks tend to yield low future returns. We examine if exposure to investor sentiment can explain the abnormal returns of the MAPs.

Panel A in Table XI reports the results of the conditional Fama-French model with monthly changes in investor sentiment. Both coefficients of the changes in the investor sentiment and the product of the market excess return with the changes in the investor sentiment are insignificant. In addition, the adjusted R^2s are virtually the same as the ones in the Fama-French three-factor model. Evidence from this panel suggests that the abnormal returns of the MAPs cannot be explained by the exposure to the investor sentiment.

Stock volatility is intimately related to default spread. Starting from Merton (1974), a number of theoretic studies such as Longstaff and Schwartz (1995); Leland and Toft (1996); Collin-Dufresne, Goldstein, and Martin (2001) use stock volatility as the most important factor driving credit risk. Many empirical studies such as Ericsson, Jacobs, and Oviedo (2009) also link stock volatility to default spread. Panel B of Table XI reports the results of regressing the MAPs on the Fama-French three factors and the default spread. Similar to the case of investor sentiment, the MAPs are insensitive to the default spread: all the coefficients are positive but insignificant.

Volatility is closely related to liquidity. Spiegel and Wang (2005) provide both theoretical reasons and empirical evidence that volatility and liquidity are negatively correlated: High volatility stocks tend to be illiquid stocks.[17] Therefore exposure to liquidity may explain the abnormal returns of the MAPs. Panel C of Table XI reports the results of regressing the MAP portfolios on the Fama-French three factors and the aggregate liquidity factor of Pástor and Stambaugh (2003). Again, both coefficients are insignificant, suggesting that liquidity premium cannot provide a good explanation for the abnormal returns of the MAPs.

Finally we put all the variables into the Fama-French conditional model and also add the recession dummy. The results are reported in Panel D. Similar to Table X, recession dummy still significantly positive, however, the coefficient of the product of recession dummy with the market is significantly negative, suggesting that the market betas of the MAPs are smaller in recession. The coefficients of the interaction term between default spread and the market become significantly positive, which suggests that the MAPs have positive exposure to the default risk: when the default spread increases, the market betas of the MAPs become larger. Nevertheless, the abnormal returns of the MAPs are still highly significant, and the magnitude is considerably large, suggesting the robustness of the profitability of the MAPs.

[17]Other studies include Benston and Hagerman (1974), Stoll (1978), and Brunnermeier and Pedersen (2008), to name a few.

VI Concluding Remarks

In this paper, we document that a standard moving average of technical analysis, when applied to portfolios sorted by volatility, can generate investment timing portfolios that outperform the buy-and-hold strategy greatly, with returns that have negative or little risk exposures on the market factor and the Fama-French SMB and HML factors. Especially for the high volatility portfolios, the abnormal returns, relative to the CAPM and the Fama and French (1993) three-factor models, are high, and higher than those from the momentum strategy. While the moving average strategy is a trend-following one similar to the momentum strategy, its performance has little correlation with the momentum strategy, and behaves differently over business cycles. Furthermore, the abnormal returns are not sensitive to changes in investor sentiment, default and liquidity risks.

Our study provides new a research avenue in several areas. First, our study suggests that it will be likely fruitful to examine the profitability of technical analysis in various markets and asset classes by investigating the cross-sectional performance, especially focusing on the role of volatility. Given the vast literature on technical analysis, potentially many open questions may be explored and answered along this direction. Second, our study presents an exciting new anomaly in the finance literature. Given the size of the abnormal returns and the wide use of technical analysis, explaining the moving average anomaly with new asset pricing models will be important and desirable. Thirdly, because of its trend-following nature, various investment issues that have been investigated around the momentum strategy can also be investigated with the moving average strategy. All of these are interesting topics for future research.

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Table I
Summary Statistics

We calculate the 10-day moving average prices each day using the last 10 days' closing prices including the current closing price, and compare the moving average price with the current price as the timing signal. If the current price is above the moving average price, it is an in-the-market signal, and we will invest in the decile portfolios for the next trading day; otherwise it is an out-of-the-market signal, and we will invest in the 30-day risk-free Treasury Bill for the next trading day. We use the 10 NYSE/Amex volatility decile portfolios as the investment assets. We report the average return (Avg Ret), the standard deviation (Std Dev), and the skewness (Skew) for the buy-and-hold benchmark decile portfolios (Panel A), the moving average timing decile portfolios (Panel B), and the moving average portfolios (MAPs) that are the differences between the MA timing portfolios and the buy-and-hold portfolios (Panel C). The results are annualized and in percentage. We also report the annualized Sharpe ratio (SRatio) for the buy-and-hold portfolios and the moving average timing portfolios, and report the success rate for the MAPs. The sample period is from July 1, 1963 to December 31, 2009.

Rank	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	Success
	Panel A				**Panel B**				**Panel C**			
	Volatility Decile Portfolios				**MA(10) Timing Portfolios**				**MAP**			
Low	10.81	6.82	-0.22	0.80	19.22	4.16	1.22	3.33	8.42	5.31	0.71	0.62
2	12.61	9.32	-0.52	0.78	21.12	5.75	0.35	2.74	8.51	7.27	0.99	0.59
3	13.96	11.14	-0.78	0.77	22.50	7.06	-0.16	2.43	8.54	8.56	1.37	0.58
4	14.64	12.77	-0.69	0.72	24.36	8.17	-0.34	2.32	9.72	9.74	1.09	0.58
5	15.10	14.35	-0.70	0.68	26.25	9.18	-0.18	2.27	11.15	10.95	1.22	0.58
6	15.99	15.39	-0.57	0.69	28.26	9.81	-0.01	2.33	12.26	11.77	1.01	0.59
7	16.10	16.71	-0.49	0.64	29.12	10.70	0.22	2.22	13.02	12.75	1.00	0.59
8	15.58	18.10	-0.37	0.56	32.35	11.61	0.54	2.32	16.77	13.76	0.95	0.59
9	18.49	19.11	-0.28	0.69	37.19	12.49	0.66	2.55	18.70	14.30	0.88	0.59
High	44.78	20.29	0.25	1.94	60.51	14.41	1.63	3.82	15.73	14.05	0.48	0.61
High - Low	33.98	17.14	0.49	0.80	41.28	13.33	1.53	3.33	7.31	11.80	0.33	0.62

Table II
CAPM and Fama-French Alphas

The table reports the alphas, betas and the adjusted R-squares of the regressions of the MAPs formed from the 10-day MA timing strategy on the market factor (Panel A) and on the Fama-French three factors (Panel B), respectively. The alphas are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by an ***, an **, and an *, respectively. The sample period is from July 1, 1963 to December 31, 2009.

Rank	α	β_{mkt}	Adj. R^2	α	β_{mkt}	β_{smb}	β_{hml}	Adj. R^2
	Panel A: CAPM			**Panel B: Fama-French**				
Low	9.31***	-0.18***	26.96	9.80***	-0.19***	-0.04**	-0.07***	28.02
	(11.88)	(-8.50)		(12.40)	(-9.04)	(-2.17)	(-3.57)	
2	10.02***	-0.30***	41.02	10.97***	-0.33***	-0.10***	-0.13***	43.33
	(10.85)	(-11.79)		(11.70)	(-12.28)	(-5.10)	(-4.73)	
3	10.42***	-0.37***	45.72	11.49***	-0.41***	-0.13***	-0.13***	48.10
	(9.91)	(-13.91)		(10.71)	(-13.84)	(-6.71)	(-4.18)	
4	11.89***	-0.43***	47.40	13.25***	-0.48***	-0.19***	-0.16***	50.60
	(10.11)	(-15.38)		(11.13)	(-15.05)	(-8.88)	(-4.39)	
5	13.62***	-0.49***	48.71	15.35***	-0.55***	-0.25***	-0.20***	53.03
	(10.89)	(-16.99)		(12.30)	(-16.43)	(-10.75)	(-4.75)	
6	14.91***	-0.52***	48.11	16.82***	-0.59***	-0.32***	-0.21***	53.53
	(10.91)	(-18.87)		(12.60)	(-18.03)	(-11.49)	(-4.94)	
7	15.89***	-0.57***	48.17	17.85***	-0.64***	-0.37***	-0.20***	54.04
	(10.81)	(-19.69)		(12.53)	(-18.55)	(-12.20)	(-4.46)	
8	19.82***	-0.61***	46.93	21.73***	-0.68***	-0.44***	-0.16***	53.38
	(12.24)	(-21.38)		(14.08)	(-19.52)	(-13.10)	(-3.53)	
9	21.76***	-0.61***	43.59	23.54***	-0.68***	-0.49***	-0.12***	50.89
	(12.51)	(-20.63)		(14.16)	(-18.74)	(-15.34)	(-2.43)	
High	18.32***	-0.52***	32.56	20.21***	-0.59***	-0.52***	-0.13***	41.08
	(9.93)	(-17.56)		(11.74)	(-16.90)	(-13.76)	(-2.80)	
High - Low	9.01***	-0.34***		10.41***	-0.40***	-0.48***	-0.06	
	(5.28)	(-16.15)		(6.43)	(-15.65)	(-13.76)	(-1.54)	

Table III
Alternative Moving Averages Lag Lengths

The table reports the average returns (Avg Ret) and the Fama-French alphas (FF α) of the MAPs when they are constructed based on 20-, 50-, 100- and 200-day moving average prices, respectively. As a control, we also report the average returns and the Fama-French alphas of the random switching strategy, which are the averages taken from 10000 repeats. The results are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by an ***, an **, and an *, respectively. The sample period is from July 1, 1963 to December 31, 2009.

Rank	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α
	MAP(20)		**MAP(50)**		**MAP(100)**		**MAP(200)**		**Random Switching**	
Low	6.55***	7.93***	4.52***	5.89***	2.48**	3.76***	1.81*	3.10***	-2.72***	-1.94***
	(7.10)	(9.71)	(4.59)	(6.68)	(2.53)	(4.17)	(1.91)	(3.55)	(0.00)	(-4.04)
2	7.00***	9.50***	4.63***	7.23***	2.58**	5.24***	1.49	4.06***	-3.62***	-2.21***
	(5.72)	(9.75)	(3.64)	(7.10)	(2.03)	(5.09)	(1.25)	(4.08)	(0.00)	(-4.23)
3	7.32***	10.30***	4.80***	7.97***	2.37	5.58***	1.91	5.08***	-4.28***	-2.48***
	(5.09)	(9.46)	(3.23)	(7.09)	(1.59)	(4.85)	(1.37)	(4.62)	(0.00)	(-4.30)
4	7.57***	11.03***	5.15***	9.00***	2.95*	6.99***	2.23	6.16***	-4.64***	-2.48***
	(4.59)	(9.02)	(3.07)	(7.26)	(1.75)	(5.58)	(1.41)	(5.06)	(0.00)	(-4.13)
5	8.30***	12.47***	5.46***	9.96***	3.09	7.95***	1.44	6.23***	-4.86***	-2.34***
	(4.43)	(9.15)	(2.87)	(7.16)	(1.63)	(5.70)	(0.80)	(4.50)	(0.00)	(-3.90)
6	9.82***	14.31***	6.20***	11.06***	3.95*	9.12***	2.00	7.08***	-5.30***	-2.54***
	(4.87)	(10.05)	(3.00)	(7.45)	(1.92)	(6.14)	(1.03)	(4.83)	(0.00)	(-3.93)
7	11.00***	15.74***	7.23***	12.36***	4.22*	9.64***	2.05	7.50***	-5.35***	-2.28***
	(5.06)	(10.46)	(3.23)	(7.88)	(1.87)	(6.00)	(0.95)	(4.66)	(0.00)	(-3.65)
8	14.19***	19.17***	9.52***	14.77***	5.77**	11.31***	2.58	8.04***	-5.12***	-1.77***
	(6.04)	(12.13)	(3.86)	(8.82)	(2.32)	(6.57)	(1.07)	(4.61)	(0.00)	(-3.17)
9	15.71***	20.78***	10.56***	15.53***	5.59**	10.78***	2.43	7.74***	-6.57***	-3.07***
	(6.42)	(12.65)	(4.07)	(8.69)	(2.10)	(5.69)	(0.94)	(4.08)	(0.00)	(-3.73)
High	13.65***	18.18***	8.52***	12.94***	2.96	7.08***	1.63	5.76***	-19.72***	-16.47***
	(5.72)	(10.42)	(3.42)	(6.99)	(1.18)	(3.54)	(0.69)	(2.89)	(0.00)	(-9.72)
High - Low	7.09***	10.25***	4.00*	7.06***	0.48	3.32*	-0.18	2.66	-17.00***	-14.53***
	(3.56)	(6.33)	(1.92)	(4.11)	(0.22)	(1.81)	(-0.09)	(1.41)	(0.00)	(-9.81)

Table IV
Size Decile Portfolios

The table reports the average returns (Avg Ret) and the Fama-French alphas (FF α) of the MAPs when they are constructed with 10 NYSE/Amex/Nasdaq value-weighted market cap decile portfolios by using 10-, 20-, 50-, 100- and 200-day moving average prices, respectively. The results are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by an ***, an **, and an *, respectively. The sample period is from July 1, 1963 to December 31, 2009.

Rank	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α
	MAP(10)		**MAP(20)**		**MAP(50)**		**MAP(100)**		**MAP(200)**	
Large	0.18	2.91**	-0.01	2.88**	0.01	3.45**	-0.34	3.42**	0.80	4.79***
	(0.09)	(2.12)	(-0.00)	(2.06)	(0.01)	(2.44)	(-0.17)	(2.38)	(0.40)	(3.27)
2	9.82***	13.70***	7.83***	11.68***	4.64**	8.85***	2.70	7.58***	0.89	5.95***
	(4.44)	(9.49)	(3.41)	(7.60)	(1.98)	(5.57)	(1.15)	(4.74)	(0.39)	(3.63)
3	10.80***	15.04***	8.65***	13.00***	5.66**	10.54***	3.36	8.88***	1.27	6.94***
	(4.76)	(10.15)	(3.68)	(8.27)	(2.35)	(6.53)	(1.42)	(5.55)	(0.55)	(4.20)
4	12.24***	16.50***	10.91***	15.39***	7.27***	12.08***	4.04*	9.45***	1.80	7.25***
	(5.37)	(11.14)	(4.70)	(10.10)	(3.02)	(7.58)	(1.70)	(5.85)	(0.78)	(4.42)
5	12.90***	17.24***	12.45***	16.86***	9.16***	14.06***	5.17**	10.70***	2.43	8.10***
	(5.65)	(11.27)	(5.49)	(11.10)	(3.92)	(8.95)	(2.23)	(6.80)	(1.05)	(4.92)
6	14.88***	19.05***	14.05***	18.37***	10.36***	15.08***	6.58***	11.90***	3.64	9.01***
	(6.78)	(12.70)	(6.42)	(12.59)	(4.55)	(9.70)	(2.89)	(7.52)	(1.63)	(5.49)
7	17.45***	20.60***	15.76***	18.98***	12.12***	15.62***	7.35***	11.11***	4.28**	8.04***
	(8.58)	(14.43)	(7.66)	(13.02)	(5.77)	(10.45)	(3.48)	(7.09)	(2.06)	(5.04)
8	19.37***	21.92***	17.73***	20.38***	13.45***	16.15***	8.31***	11.27***	4.67**	7.54***
	(9.94)	(15.50)	(8.93)	(14.23)	(6.56)	(10.64)	(3.98)	(7.01)	(2.26)	(4.57)
9	20.11***	22.37***	18.15***	20.44***	13.79***	16.08***	9.00***	11.52***	4.94**	7.24***
	(10.56)	(15.68)	(9.50)	(14.16)	(6.94)	(10.50)	(4.45)	(7.06)	(2.46)	(4.30)
Small	19.86***	21.87***	18.37***	20.39***	13.52***	15.42***	8.20***	10.34***	3.24	5.22***
	(10.18)	(14.39)	(9.23)	(12.96)	(6.50)	(8.93)	(3.83)	(5.58)	(1.50)	(2.73)
Small-Large	19.68***	18.97***	18.38***	17.51***	13.51***	11.97***	8.54***	6.92***	2.44	0.43
	(10.66)	(10.97)	(9.79)	(9.93)	(6.83)	(6.44)	(4.14)	(3.49)	(1.12)	(0.21)

Table V
Size Anomaly in Recent Periods

The table reports the alphas, betas and the adjusted R-squares of the CAPM regressions of the size decile portfolios (Panel A), the 10-day MAPs (Panel B), respectively, on the market factor over the period from January 02, 2004 to December 31, 2009. The alphas are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by an ***, an ** and an *, respectively.

Period January 02, 2004 - December 31, 2009						
Rank	α	β_{mkt}	Adj. R^2	α	β_{mkt}	Adj. R^2
	Panel A: Size Deciles			**Panel B: MAP**		
Large	-0.46	0.99***	99.64	10.82***	-0.18***	21.03
	(-0.93)	(216.82)		(2.92)	(-3.20)	
2	3.38*	1.06***	95.47	5.75	-0.36***	45.67
	(1.79)	(68.09)		(1.40)	(-5.86)	
3	1.68	1.11***	91.89	1.04	-0.44***	52.41
	(0.66)	(40.20)		(0.23)	(-6.74)	
4	2.25	1.07***	89.53	0.58	-0.54***	55.99
	(0.78)	(35.06)		(0.11)	(-7.66)	
5	-0.28	1.06***	88.49	2.56	-0.66***	59.18
	(-0.09)	(38.38)		(0.48)	(-9.17)	
6	0.43	0.99***	86.59	0.83	-0.70***	60.05
	(0.13)	(35.08)		(0.15)	(-10.20)	
7	1.51	0.69***	77.42	0.11	-0.73***	58.45
	(0.36)	(28.45)		(0.02)	(-9.80)	
8	-0.02	0.51***	62.34	7.47	-0.72***	56.85
	(-0.00)	(17.84)		(1.22)	(-10.29)	
9	1.65	0.42***	44.92	11.69*	-0.69***	51.79
	(0.27)	(14.26)		(1.65)	(-8.77)	
Small	7.41	0.36***	31.50	19.84***	-0.61***	44.62
	(1.05)	(11.43)		(2.89)	(-9.25)	
Small-Large	7.87	-0.63***		9.02	-0.43***	
	(1.07)	(-17.85)		(1.33)	(-7.44)	

Table VI
Trading Frequency and Break-Even Transaction Cost

The table reports the average consecutive holding days (Holding), fraction of trading days (Trading) and the break-even transaction costs in basis point (BETC) of the MAPs when they are constructed with 10 NYSE/Amex volatility decile portfolios by using 10-, 20-, 50-, 100- and 200-day moving average prices, respectively. The break-even transaction costs are calculated such that the average returns of the MAPs are zero. The sample period is from July 1, 1963 to December 31, 2009.

Rank	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC
	MA(10)			**MA(20)**			**MA(50)**			**MA(100)**			**MA(200)**		
Low	10.50	0.19	56.81	17.28	0.12	81.61	34.03	0.06	111.52	52.03	0.04	50.92	73.76	0.03	64.77
2	10.41	0.19	64.47	16.07	0.12	80.24	32.78	0.06	104.09	53.78	0.04	78.36	82.76	0.02	47.29
3	10.37	0.19	57.44	15.45	0.13	75.75	29.88	0.07	92.68	50.83	0.04	82.94	73.36	0.03	56.35
4	10.05	0.20	43.48	15.71	0.13	57.74	29.08	0.07	63.73	49.28	0.04	62.83	69.57	0.03	43.51
5	10.23	0.20	42.22	15.56	0.13	52.98	28.11	0.07	55.87	45.77	0.04	59.58	81.35	0.02	41.95
6	9.86	0.20	37.55	15.13	0.13	44.41	27.70	0.07	50.62	44.28	0.05	43.52	71.27	0.03	33.80
7	9.17	0.22	32.49	14.79	0.14	38.00	26.33	0.08	48.01	43.45	0.05	48.09	66.16	0.03	76.35
8	9.39	0.21	28.80	15.01	0.13	40.89	27.16	0.07	49.97	44.94	0.04	36.08	73.57	0.03	61.24
9	8.76	0.23	29.61	13.79	0.15	40.71	25.68	0.08	53.79	39.19	0.05	45.25	73.32	0.03	38.31
High	7.43	0.27	33.55	10.94	0.18	43.29	19.38	0.10	62.85	32.51	0.06	51.77	58.97	0.03	63.18

Table VII
Subperiods

The table reports the alphas, betas and the adjusted R-squares of the regressions of the MAPs, formed from the 10-day MA timing strategy, on the market factor and on the Fama-French three factors, respectively, over two equally divided subperiods: from July 1, 1963 to September 30, 1986 (Panel A) and from October 1, 1986 to December 31, 2009 (Panel B). The alphas are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by an ***, an ** and an *, respectively.

Panel A: Period July 01, 1963 - September 30, 1986

Rank	α	β_{mkt}	Adj. R^2	α	β_{mkt}	β_{smb}	β_{hml}	Adj. R^2
	Panel A1: CAPM			**Panel A2: Fama-French**				
Low	11.27***	-0.24***	39.99	12.72***	-0.29***	-0.21***	-0.09***	47.74
	(11.72)	(-19.43)		(13.96)	(-21.41)	(-13.06)	(-4.44)	
2	13.36***	-0.33***	43.30	14.88***	-0.38***	-0.28***	-0.06***	51.11
	(11.98)	(-21.24)		(14.38)	(-22.94)	(-14.66)	(-2.65)	
3	15.05***	-0.38***	44.56	16.84***	-0.44***	-0.34***	-0.07***	53.19
	(11.94)	(-23.26)		(14.56)	(-24.90)	(-15.38)	(-2.56)	
4	17.32***	-0.43***	44.60	19.34***	-0.50***	-0.43***	-0.05*	55.06
	(11.90)	(-21.88)		(14.79)	(-24.74)	(-15.68)	(-1.75)	
5	19.12***	-0.48***	44.82	21.28***	-0.55***	-0.49***	-0.04	56.32
	(12.21)	(-22.72)		(15.28)	(-25.55)	(-16.76)	(-1.16)	
6	20.82***	-0.53***	43.74	23.32***	-0.61***	-0.57***	-0.04	56.26
	(11.72)	(-20.92)		(14.91)	(-24.69)	(-15.44)	(-1.12)	
7	21.96***	-0.58***	43.44	24.60***	-0.66***	-0.64***	-0.03	56.40
	(11.32)	(-20.93)		(14.49)	(-24.65)	(-15.46)	(-0.65)	
8	25.41***	-0.65***	42.49	28.34***	-0.74***	-0.75***	-0.01	56.41
	(11.41)	(-19.89)		(14.70)	(-23.95)	(-14.74)	(-0.18)	
9	26.20***	-0.66***	39.62	29.23***	-0.75***	-0.81***	0.01	54.35
	(11.16)	(-18.22)		(14.27)	(-23.24)	(-15.35)	(0.15)	
High	22.55***	-0.60***	31.16	25.95***	-0.70***	-0.92***	0.01	49.13
	(8.71)	(-15.61)		(11.62)	(-21.67)	(-15.43)	(0.21)	
High - Low	11.27***	-0.35***		13.23***	-0.41***	-0.71***	0.10**	
	(4.89)	(-11.55)		(6.28)	(-15.16)	(-13.25)	(2.11)	

Panel B: Period October 01, 1986 - December 31, 2009								
Rank	α	β_{mkt}	Adj. R^2	α	β_{mkt}	β_{smb}	β_{hml}	Adj. R^2
	Panel B1: CAPM			**Panel B2: Fama-French**				
Low	7.39***	-0.15***	21.30	7.69***	-0.16***	0.02	-0.07***	22.69
	(6.16)	(-4.78)		(6.39)	(-5.21)	(0.87)	(-3.38)	
2	6.71***	-0.29***	39.98	7.37***	-0.31***	-0.03	-0.15***	42.49
	(4.63)	(-7.79)		(5.14)	(-8.37)	(-1.09)	(-4.69)	
3	5.82***	-0.37***	46.31	6.50***	-0.39***	-0.05**	-0.15***	48.24
	(3.51)	(-9.59)		(3.95)	(-9.81)	(-2.02)	(-3.93)	
4	6.50***	-0.43***	48.75	7.37***	-0.46***	-0.09***	-0.19***	51.25
	(3.56)	(-10.84)		(4.09)	(-10.92)	(-3.74)	(-4.29)	
5	8.15***	-0.49***	50.51	9.30***	-0.54***	-0.15***	-0.25***	54.14
	(4.23)	(-12.22)		(4.98)	(-12.26)	(-5.37)	(-4.81)	
6	9.03***	-0.52***	50.34	10.26***	-0.58***	-0.22***	-0.26***	54.74
	(4.40)	(-13.48)		(5.22)	(-13.29)	(-6.03)	(-5.06)	
7	9.85***	-0.56***	50.70	11.06***	-0.62***	-0.27***	-0.25***	55.21
	(4.51)	(-14.03)		(5.29)	(-13.64)	(-6.67)	(-4.68)	
8	14.29***	-0.59***	49.84	15.38***	-0.64***	-0.32***	-0.21***	54.47
	(6.14)	(-14.92)		(6.96)	(-14.00)	(-7.69)	(-3.86)	
9	17.37***	-0.58***	46.32	18.27***	-0.64***	-0.37***	-0.16***	51.42
	(6.80)	(-14.48)		(7.50)	(-13.41)	(-9.57)	(-2.77)	
High	14.16***	-0.48***	34.19	15.14***	-0.54***	-0.37***	-0.18***	39.91
	(5.43)	(-11.79)		(6.15)	(-11.50)	(-7.90)	(-3.26)	
High - Low	6.77***	-0.33***		7.45***	-0.38***	-0.39***	-0.11**	
	(2.69)	(-12.19)		(3.12)	(-11.80)	(-8.40)	(-2.23)	

Table VIII
Market Timing

The table reports the alphas, betas and the adjusted R-squares of the market timing regressions of the MAPs. Panel A is Treynor and Mazuy (1966) quadratic regression with the squared market factor (β_{mkt^2}), and Panel B is Henriksson and Merton (1981) regression with option-like returns on the market (γ_{mkt}), respectively. The alphas are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by an ***, an **, and an *, respectively. The sample period is from July 1, 1963 to December 31, 2009.

Rank	α	β_{mkt}	β_{mkt^2}	Adj. R^2	α	β_{mkt}	γ_{mkt}	Adj. R^2
	Panel A: TM Regression				**Panel B: HM Regression**			
Low	7.09***	-0.17***	0.91	28.24	1.74	-0.22***	0.09**	26.93
	(3.84)	(-8.51)	(1.22)		(0.57)	(-7.49)	(2.27)	
2	7.87***	-0.29***	0.88	41.61	2.58	-0.34***	0.09*	40.96
	(3.77)	(-12.11)	(1.00)		(0.72)	(-9.06)	(1.86)	
3	8.51***	-0.37***	0.78	46.04	3.57	-0.41***	0.08*	45.67
	(4.02)	(-14.62)	(0.86)		(0.97)	(-10.08)	(1.64)	
4	10.24***	-0.43***	0.68	47.55	4.89	-0.47***	0.08*	47.34
	(4.93)	(-15.85)	(0.76)		(1.30)	(-11.54)	(1.62)	
5	11.29***	-0.49***	0.95	48.98	3.68	-0.55***	0.12***	48.64
	(6.95)	(-17.19)	(1.54)		(1.09)	(-13.52)	(2.47)	
6	12.95***	-0.52***	0.80	48.24	5.50*	-0.58***	0.11**	48.04
	(8.33)	(-18.97)	(1.46)		(1.71)	(-15.15)	(2.43)	
7	14.02***	-0.56***	0.76	48.26	7.52**	-0.62***	0.10**	48.11
	(8.61)	(-19.73)	(1.42)		(2.34)	(-15.81)	(2.16)	
8	17.68***	-0.60***	0.88*	47.04	9.06***	-0.67***	0.13***	46.86
	(10.32)	(-21.88)	(1.68)		(2.83)	(-17.65)	(2.84)	
9	19.65***	-0.60***	0.86	43.69	9.05***	-0.68***	0.15***	43.53
	(10.33)	(-21.04)	(1.35)		(2.49)	(-17.67)	(2.98)	
High	16.01***	-0.51***	0.95	32.72	6.73*	-0.58***	0.14***	32.53
	(7.53)	(-17.73)	(1.48)		(1.81)	(-15.48)	(2.75)	
High - Low	8.92***	-0.34***	0.04		4.98	-0.36***	0.05	
	(4.55)	(-15.90)	(0.07)		(1.45)	(-11.95)	(1.06)	

Table IX
Relative to Momentum

The table reports the alphas, betas and the adjusted R-squares of the regressions of the MAPs, formed from the 10-day MA timing strategy, on the Fama-French three factors and the momentum factor. The alphas are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by an ***, an **, and an *, respectively. The sample period is from July 1, 1963 to December 31, 2009.

Rank	α	β_{mkt}	β_{smb}	β_{hml}	β_{umd}	Adj. R^2	ΔR^2
Low	10.42***	-0.20***	-0.04**	-0.09***	-0.06***	29.28	1.26
	(12.59)	(-9.32)	(-2.23)	(-4.87)	(-4.00)		
2	11.60***	-0.34***	-0.10***	-0.15***	-0.06***	44.02	0.69
	(11.88)	(-12.40)	(-5.17)	(-6.01)	(-3.01)		
3	12.28***	-0.42***	-0.13***	-0.16***	-0.07***	48.88	0.78
	(11.07)	(-14.16)	(-6.74)	(-5.60)	(-3.36)		
4	14.04***	-0.49***	-0.19***	-0.19***	-0.07***	51.20	0.60
	(11.52)	(-15.49)	(-8.94)	(-5.67)	(-3.24)		
5	16.06***	-0.56***	-0.25***	-0.23***	-0.06***	53.41	0.38
	(12.64)	(-17.08)	(-10.75)	(-5.99)	(-2.71)		
6	17.64***	-0.60***	-0.32***	-0.24***	-0.07***	53.97	0.44
	(13.03)	(-18.95)	(-11.33)	(-6.33)	(-3.04)		
7	18.65***	-0.65***	-0.37***	-0.23***	-0.07***	54.39	0.35
	(12.88)	(-19.46)	(-12.04)	(-5.70)	(-2.88)		
8	22.65***	-0.69***	-0.44***	-0.20***	-0.08***	53.79	0.41
	(14.36)	(-20.46)	(-13.00)	(-4.73)	(-2.93)		
9	24.31***	-0.69***	-0.49***	-0.15***	-0.07**	51.16	0.27
	(14.32)	(-19.71)	(-15.35)	(-3.25)	(-2.36)		
High	21.04***	-0.60***	-0.52***	-0.16***	-0.08**	41.40	0.32
	(11.92)	(-17.50)	(-13.87)	(-3.71)	(-2.38)		
High - Low	10.62***	-0.40***	-0.48***	-0.07*	-0.02		
	(6.43)	(-16.44)	(-13.76)	(-1.84)	(-0.75)		

Table X
Business Cycles and Up Markets

Panel A of the table reports the regression results of the NYSE/Amex MAPs, formed from the 10-day MA timing strategy, on the Fama-French market portfolio, SMB and HML factors, and an NBER recession dummy variable, as well as the same regression with the momentum factor, UMD, as the dependent variable. Panel B of the table reports similar regression results when an up market dummy variable is used which indicates whether the last year market return is positive. Both the intercepts and the coefficients on the dummy variables are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by an ***, an **, and an *, respectively. The sample period is from July 1, 1963 to December 31, 2009.

Decile	α	β_{mkt}	β_{smb}	β_{hml}	Recession	Adj. R^2	α	β_{mkt}	β_{smb}	β_{hml}	Up Market	Adj. R^2
	Panel A: With Recession Dummy						**Panel B: With Up Market Dummy**					
Low	8.05***	-0.19***	-0.04**	-0.07***	10.70***	28.23	10.82***	-0.19***	-0.04**	-0.07***	-1.32	27.90
	(11.46)	(-8.69)	(-2.19)	(-3.47)	(3.39)		(7.02)	(-8.64)	(-2.19)	(-3.42)	(-0.76)	
2	9.11***	-0.33***	-0.10***	-0.13***	11.33***	43.46	12.44***	-0.33***	-0.10***	-0.13***	-1.94	43.23
	(10.61)	(-11.77)	(-5.18)	(-4.57)	(3.16)		(6.42)	(-11.70)	(-5.15)	(-4.53)	(-0.92)	
3	9.68***	-0.41***	-0.13***	-0.13***	11.06***	48.19	15.06***	-0.41***	-0.13***	-0.13***	-4.76**	48.04
	(9.64)	(-13.77)	(-6.61)	(-4.44)	(2.92)		(7.01)	(-13.71)	(-6.58)	(-4.40)	(-2.03)	
4	11.32***	-0.48***	-0.18***	-0.16***	11.77***	50.67	18.14***	-0.48***	-0.19***	-0.16***	-6.60***	50.55
	(10.36)	(-15.12)	(-8.75)	(-4.65)	(2.80)		(7.62)	(-15.04)	(-8.71)	(-4.62)	(-2.53)	
5	13.07***	-0.55***	-0.25***	-0.20***	13.94***	53.12	20.22***	-0.55***	-0.25***	-0.20***	-6.52**	52.96
	(11.26)	(-16.05)	(-10.74)	(-4.79)	(3.05)		(7.84)	(-15.93)	(-10.72)	(-4.75)	(-2.33)	
6	14.77***	-0.59***	-0.32***	-0.21***	12.53***	53.59	20.36***	-0.59***	-0.32***	-0.21***	-4.72	53.43
	(11.76)	(-17.65)	(-11.22)	(-5.01)	(2.56)		(6.86)	(-17.50)	(-11.20)	(-4.96)	(-1.49)	
7	15.69***	-0.64***	-0.37***	-0.20***	13.21***	54.09	21.53***	-0.64***	-0.37***	-0.20***	-4.87	53.97
	(11.56)	(-18.24)	(-11.96)	(-4.52)	(2.58)		(6.92)	(-18.10)	(-11.92)	(-4.47)	(-1.46)	
8	19.05***	-0.68***	-0.44***	-0.16***	16.32***	53.45	26.65***	-0.68***	-0.44***	-0.16***	-6.55*	53.31
	(13.04)	(-19.10)	(-12.66)	(-3.58)	(3.05)		(7.85)	(-18.93)	(-12.64)	(-3.51)	(-1.80)	
9	20.72***	-0.68***	-0.49***	-0.12***	17.19***	50.97	29.78***	-0.68***	-0.49***	-0.12***	-8.20**	50.82
	(13.48)	(-19.24)	(-15.09)	(-2.58)	(2.93)		(8.36)	(-19.08)	(-15.05)	(-2.53)	(-2.13)	
High	17.81***	-0.59***	-0.52***	-0.13***	14.69***	41.14	25.78***	-0.59***	-0.52***	-0.13***	-7.20*	41.07
	(10.61)	(-16.05)	(-13.78)	(-2.71)	(2.44)		(6.75)	(-15.96)	(-13.73)	(-2.69)	(-1.75)	
UMD	12.24***	-0.17***	-0.01	-0.41***	-6.99	9.11	3.09	-0.17***	-0.00	-0.41***	10.86**	9.45
	(6.19)	(-5.48)	(-0.16)	(-6.59)	(-0.92)		(0.63)	(-5.60)	(-0.07)	(-6.68)	(2.03)	

Table XI
Conditional Models with Sentiment, Default Spread, Liquidity, and Recession Dummy

This table reports the regression results of the NYSE/Amex MAPs, formed from the 10-day MA timing strategy, using conditional Fama-French three-factor models:

$$\text{MAP}_{jt,L} = \alpha_j + \beta_{j,mkt} r_{mkt,t} + \beta_{j,smb} r_{smb,t} + \beta_{j,hml} r_{hml,t} + \beta_{j,Z} Z_{t-1} + \gamma_{j,S} Z_{t-1} r_{mkt,t} + \epsilon_{jt},$$

Panel A reports the results with the changes in investor Sentiment (Baker and Wurgler, 2006), Panel B reports the results with the default spread, which is the yield difference between BAA and AAA corporate bonds, Panel C reports the results with the liquidity tradable factor (Pástor and Stambaugh, 2003), and Panel D reports the results with all three variables above plus recession dummy. The Fama-French alphas are annualized and in percentage, and the other coefficients are also scaled for ease of presentation. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% level is given by an ***, an ** and an *, respectively. The sample period in Panel A is from July 1, 1965 to December 31, 2007, in Panel C is from July 1, 1968 to December 31, 2009, and in Panel D is from July 1, 1968 to December 31, 2007 due to data availability.

Decile	FF α	ΔSent	ΔSent$\times r_{mkt}$	Adj. R^2	FF α	Default	Default$\times r_{mkt}$	Adj. R^2	FF α	Liquid	Liquid$\times r_{mkt}$	Adj. R^2
	Panel A: Sentiment				**Panel B: Default Spread**				**Panel C: Liquidity**			
Low	10.13***	0.56	-0.68	33.19	9.48***	0.47	5.82***	29.19	9.90***	0.84	0.44	27.62
	(13.38)	(0.80)	(-0.64)		(4.55)	(0.22)	(3.39)		(10.89)	(0.26)	(0.74)	
2	11.58***	1.19	-1.16	44.55	10.13***	0.95	4.95*	43.78	11.24***	-3.23	0.77	43.60
	(12.87)	(1.38)	(-0.85)		(3.77)	(0.34)	(1.91)		(10.63)	(-0.79)	(1.11)	
3	12.53***	1.41	-1.65	48.69	10.91***	0.69	4.28	48.34	11.62***	-2.91	0.70	48.13
	(12.17)	(1.37)	(-1.10)		(3.74)	(0.23)	(1.31)		(9.82)	(-0.69)	(1.00)	
4	14.28***	1.68	-1.13	50.37	12.32***	1.01	4.15	50.77	13.31***	-1.55	0.87	50.77
	(12.70)	(1.44)	(-0.73)		(3.94)	(0.32)	(1.07)		(10.15)	(-0.33)	(1.21)	
5	15.71***	1.72	-1.22	51.50	12.77***	2.54	2.40	53.08	15.54***	-3.57	1.05	53.29
	(13.34)	(1.35)	(-0.77)		(3.49)	(0.67)	(0.53)		(11.16)	(-0.73)	(1.45)	
6	17.64***	2.70**	-0.80	51.97	15.33***	1.48	1.40	53.54	17.09***	-2.49	1.02	53.70
	(13.85)	(1.99)	(-0.49)		(3.83)	(0.36)	(0.30)		(11.67)	(-0.48)	(1.45)	
7	18.92***	2.07	-0.15	53.12	18.46***	-0.50	2.81	54.08	18.10***	-3.23	0.91	54.05
	(13.88)	(1.39)	(-0.09)		(4.37)	(-0.12)	(0.56)		(11.60)	(-0.58)	(1.18)	
8	22.71***	2.25	-0.64	52.99	18.23***	3.53	5.95	53.56	22.00***	-0.63	0.43	53.13
	(15.24)	(1.33)	(-0.32)		(4.13)	(0.80)	(1.15)		(13.35)	(-0.11)	(0.55)	
9	24.64***	1.36	0.61	50.78	19.22***	4.37	7.30	51.15	23.96***	-0.59	0.36	50.61
	(15.57)	(0.76)	(0.30)		(4.23)	(0.97)	(1.41)		(13.33)	(-0.09)	(0.47)	
High	20.86***	1.92	0.42	40.28	16.81***	3.48	7.16	41.33	20.95***	-2.10	0.06	40.72
	(12.22)	(0.97)	(0.18)		(3.57)	(0.76)	(1.47)		(11.22)	(-0.32)	(0.08)	
High - Low	10.73***	1.37	1.10		7.33*	3.01	1.33		11.05***	-2.95	-0.38	
	(6.81)	(0.74)	(0.68)		(1.66)	(0.71)	(0.32)		(6.36)	(-0.51)	(-0.69)	

Panel D: Sentiment, Default Spread, Liquidity, and Recession Dummy

Decile	FF α	ΔSent	Default	Liquid	Rec	ΔSent$\times r_{mkt}$	Default$\times r_{mkt}$	Liquid$\times r_{mkt}$	Rec$\times r_{mkt}$	Adj. R^2
Low	12.26***	0.68	-0.02	140.35**	7.59***	-0.75	0.03	-0.50	-0.09***	34.50
	(6.29)	(0.97)	(-0.85)	(2.03)	(2.64)	(-0.88)	(1.51)	(-0.82)	(-3.88)	
2	10.55***	1.39	0.00	55.12	10.91***	-1.35	0.06**	-0.39	-0.11***	45.48
	(4.45)	(1.57)	(0.17)	(0.65)	(3.38)	(-1.23)	(2.10)	(-0.51)	(-3.98)	
3	10.38***	1.64	0.01	23.25	13.15***	-1.81	0.07**	-0.28	-0.10***	49.18
	(3.78)	(1.55)	(0.37)	(0.24)	(3.70)	(-1.44)	(2.39)	(-0.35)	(-3.24)	
4	13.17***	2.02*	-0.01	-9.53	16.51***	-1.38	0.08***	-0.16	-0.11***	50.84
	(4.21)	(1.66)	(-0.34)	(-0.09)	(4.20)	(-1.01)	(2.55)	(-0.20)	(-2.98)	
5	12.97***	2.02	0.01	22.65	16.96***	-1.41	0.09***	-0.24	-0.11***	51.90
	(3.97)	(1.53)	(0.19)	(0.21)	(4.11)	(-1.00)	(2.55)	(-0.31)	(-3.03)	
6	13.77***	3.07**	0.01	64.64	15.20***	-1.12	0.09***	0.09	-0.11***	52.28
	(3.78)	(2.17)	(0.41)	(0.55)	(3.24)	(-0.75)	(2.46)	(0.11)	(-2.69)	
7	17.38***	2.34	-0.02	20.16	18.35***	-0.43	0.10***	0.01	-0.13***	53.49
	(4.45)	(1.53)	(-0.48)	(0.16)	(3.77)	(-0.28)	(2.71)	(0.02)	(-2.98)	
8	19.13***	2.57	0.00	75.23	17.94***	-0.90	0.11***	-0.21	-0.18***	53.56
	(4.35)	(1.45)	(0.01)	(0.55)	(3.30)	(-0.50)	(2.76)	(-0.24)	(-3.47)	
9	22.24***	1.69	-0.01	66.75	16.41***	0.26	0.13***	-0.19	-0.19***	51.41
	(4.84)	(0.91)	(-0.19)	(0.46)	(2.82)	(0.14)	(2.93)	(-0.20)	(-3.35)	
High	21.82***	1.81	0.00	45.27	10.13	0.07	0.13***	-0.46	-0.14**	40.55
	(4.51)	(0.86)	(0.00)	(0.30)	(1.61)	(0.03)	(3.19)	(-0.42)	(-2.36)	
High - Low	9.56**	1.13	0.02	-95.08	2.55	0.82	0.10***	0.03	-0.04	
	(2.08)	(0.57)	(0.42)	(-0.71)	(0.44)	(0.52)	(3.13)	(0.05)	(-0.92)	