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

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Abstract

In this paper, we document that an application of the moving averages (a popular form of technical analysis) to portfolios sorted by volatility generates 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 SML and HML factors. As a result, 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 for high decile portfolios. The abnormal returns remain high even after accounting for transaction costs. While the moving average is a trend-following strategy as the momentum, its performance has little correlation with the momentum, and behaves differently over business cycles, default and liquidity risks.

JEL Classification:

keywords: Technical Analysis, Moving Average, Anomaly, Market Timing

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 the 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 with empirical studies go at least back to 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 of using technical analysis, primarily the moving averages, to forecast the market. Although Sullivan, Timmermann, and White (1999) show that Brock et al.'s (1992) results are much weakened after 1987, the consensus appears that technical analysis is useful in making investment decisions. Zhu and Zhou (2009) further demonstrate that technical analysis can be a valuable learning tool about the uncertainty of market dynamics.

Our paper provides what appears 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 motivations for our study 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, the other signals are likely imprecise, and hence the investors tend to rely more on the technical signal than before. Hence, if there is truly profitability of technical analysis, this profitability is likely to show up for high volatility stocks than for low volatility ones. Second, theoretical models, such as Brown and Jennings (1989), show that rational investors can gain from forming expectations based on historical prices and the gain is an increasing function of the volatility of the asset. Third, our use of technical analysis focus on applying the popular moving averages to time investments. This is a trend-following strategy, and hence our profitability analysis 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 underreaction 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) to 10 volatility decile portfolios formed from stocks traded on the Nasdaq by computing the 10-day average prices of the decile portfolios. 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 on 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 positive and increasing with volatility decile, ranging from 5.17% (annualized) to 18.55%. Moreover, the CAPM risk-adjusted or abnormal returns are also strictly increasing with volatility decile, ranging from 6.17% to 20.56%. The Fama-French model risk-adjusted returns also vary monotonically from 7.49% to 21.38%. In addition, the betas are either negatively 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. For example, they range from 7.85% to 20.51% across the deciles when $L = 20$, and remain over 5% when $L = 200$. Second, we also apply the same MA timing strategy to three alternative sets of decile portfolios. With 10 volatility decile portfolios either formed by using stocks traded on the NYSE/Amex instead of Nasdaq or by using NYSE stocks only, we find that the same qualitative results hold, with abnormal returns on the MAPs relative to the Fama-French model ranging from 9.83% to 20.29% for the NYSE/Amex portfolios, and from 10.62% to 18.81% for the NYSE portfolios without the first decile. With the commonly used value-weighted size decile portfolios from NYSE/Amex/Nasdaq, which are a proxy of the volatility deciles, we obtain similar results as: the abnormal returns relative to the Fama-French model range from 13.70% to 21.87% without the last decile. Third, we examine whether the abnormal returns can go away once transaction costs are incorporated. With a cost of 25 basis points each trade, the transaction costs do make the abnormal returns smaller than before, but those on the last 5 decile portfolios are still over 9.98%, a magnitude of great economic importance. 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 seems the only one that is persistent and survived after 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. Note that the momentum anomaly earns roughly about 12% annually, substantially smaller than the abnormal returns on the largest volatility decile portfolio. However, 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 0.0375 to 0.1513 from the lowest Nasdaq decile MAP to the highest Nasdaq 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 the recession. In contrast, the momentum strategy generates much smaller risk-adjusted abnormal returns in recession periods. Moreover, they respond quite differently to default and liquidity risks. In short, despite of trend-following by both, the MAP and the momentum are two distinct anomalies.[1]

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

I The Moving Average Timing Strategies

We use three sets of 10 volatility decile portfolios and a set of 10 size decile portfolios in this paper. All of the data are readily available from the Center for Research in Security

[1] Han and Zhou (2010) explore how technical analysis can help to improve the popular momentum strategy.

Prices (CRSP). More specifically, the first set is constructed based on Nasdaq stocks sorted into ten groups (deciles) by their annual standard deviations using the daily returns within the year.[2] Once stocks are assigned to portfolios, portfolio index levels (prices) and daily returns are calculated via equal-weighting.[3] The portfolios are rebalanced each year at the end of the previous year. The second set of volatility decile portfolios is constructed similarly but with NYSE/Amex stocks instead. The Nasdaq volatility decile portfolio returns span from January 2 of 1973 to December 31 of 2009, while the NYSE/Amex volatility decile portfolio returns span from July 1 of 1963 to December 31 of 2009. The third set of volatility decile portfolios is constructed similarly but with NYSE stocks only. The fourth set is 10 value-weighted size decile portfolios sorted by firm size with stocks traded on the NYSE/Amex/Nasdaq. The sample period is from July 1, 1963 to December 31, 2009.

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 et al. (1992), we consider 10-, 20-, 50-, 100- and 200-day moving averages in this paper. The MA is the most popular way of using technical analysis and is the focus of study in the literature. Consider the trading decision with the use of the 10-day moving average, for example. 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 strategy. 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 get out of the asset. Its theoretical reasons and empirical evidence will be examined in the next section.

[2] In CRSP, portfolio 1 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 1 contains the stocks with the lowest standard deviation.

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

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 ten decile portfolios, we thus obtain ten MAPs,

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

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.

II Profitability of the Moving Average Portfolios

In this section, we provide first the summary statistics of the volatility decile portfolios, the MA timing portfolios, and the MAPs, and then the alphas 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 MA timing portfolios, $\tilde{R}_{jt,L}$, and the returns on the MAPs, $\text{MAP}_{jt,L}$. Panel A provides the average returns and standard deviations of the buy-and-hold strategy across the ten volatility deciles. The returns are an increasing function of the decile, ranging from 14.91%

per annum for the lowest decile to 70.62% per annum for the highest decile.[4] Similarly, the MA timing portfolios, reported in Panel B, also have returns varying positively with decile, ranging from 20.06% to 89.12%. However, the returns on the MA timing portfolios are not only larger than that on the decile portfolios, but also enjoy substantially smaller standard deviations. For example, the standard deviation is 5.06% versus 7.75% for the lowest decile portfolio, and 15.31% versus 20.65% for the highest decile portfolio. In general, the MA timing strategy yields only about 65% volatility of the decile portfolios. Panel C reports the results for the MAPs. The returns increase monotonically from 5.17% to 18.55% across the deciles. While the standard deviations are much smaller than those of R_{jt} in the corresponding deciles, they are not much different from those of $\tilde{R}_{jt,L}$.

The simple summary statistics clearly show that the MA timing performs well. The MA timing portfolios outperform decile portfolios with higher Sharpe ratios by having higher average returns and lower standard deviations. But 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. Note that there are great differences in the average returns across the volatility decile portfolios. Ang, Hodrick, Xing, and Zhang (2006), among others, examine whether these differences can be explained by rational asset pricing models. In contrast, we focus here on the MAPs, which measure the relative performance of the MA timing strategy to the buy-and-hold strategy.

B Alpha

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

$$\mathrm{MAP}_{jt,L} = \alpha_j + \beta_{j,mkt}(R_{mkt,t} - r_{ft}) + \epsilon_t, \qquad j = 1, \dots, 10, \tag{4}$$

where $R_{mkt,t}$ is the return on market. Panel A of Table II reports the results of the daily market model regressions.[5] The alphas or risk-adjusted returns are even greater than the

[4]The returns appear very high, but they are indeed so because the equal-weighted Nasdaq market index has an *annualized* average return and a standard deviation of 23.66% and 13.71% over the sample period. Moreover, if one annualizes the realized monthly returns on the portfolios, the results will be similar to those reported in Table I.

[5]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 6.65%, 7.74%, 11.40%, 14.37%, 17.46%, 20.58%, 23.09%, 25.51%, 26.13% and 22.61% with monthly regressions. They are very close and slightly higher than those in Table II.

unadjusted ones, ranging from 6.17% to 23.93%. The alphas increase monotonically from the lowest volatility decile to higher volatility deciles. However, the highest decile yields a slightly lower alpha than the 9th decile. Nevertheless, the highest volatility decile generates an alpha that is about 3.33 (20.56/6.17) times as large as that generated by the lowest decile.

The large risk-adjusted abnormal returns show clearly 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. The intuition can be understood as follows. The MA timing strategy is designed to avoid the downfall of the portfolios. When the portfolios is down and the market is most likely down too, because of its successful timing ability, the MA timing portfolios have much smaller market betas than the underlying volatility decile portfolios. When the portfolio is up and the market is most likely up, the MA may have false signals,then the MA timing portfolios have smaller betas than the underlying volatility decile portfolios too. As a result, the market betas of the MAPs are negative.

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

$$\mathrm{MAP}_{jt,L} = \alpha_j + \beta_{j,mkt}(R_{mkt,t} - r_{ft}) + \beta_{j,smb}R_{smb,t} + \beta_{j,hml}R_{hml,t} + \epsilon_t, \qquad j = 1, \ldots, 10. \quad (5)$$

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 even more negative than in the CAPM case. Interestingly, all the betas on the SMB factor are negative too. This is again due to less exposure of the MA timing strategy to the SMB factor. Not surprisingly, the volatility decile portfolios have very high exposure to the SMB factor because small stocks often have high volatility. In addition, the betas on the HML factor are either negatively small or negligible. These results suggest that MAPs are excellent portfolios for investors to hold to hedge risks of the market portfolio and of the SMB factor without adding much exposure to the HML factor. On model fitting, similar to other studies, the three-factor model does have better explanatory power than the CAPM, with the adjusted R^2s in the three-factor model are about 10% higher than those in the CAPM case across the deciles.

C Explanations

The large alphas provided in the previous subsection clearly indicates the profitability of using technical analysis, the MA strategy in particular. 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 prices in the 70s, a random walk model and the like are commonly used, in which the stock return is assumed 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 predictability. Many recent theoretical models allow predictability too (see, e.g., Cochrane, 2008, and the references therein). The predictability of stock returns permits the possibility of profitable technical rules.

Indeed, Brock et al. (1992) provide strong evidence on the profitability of using the MA to predict the Dow Jones Index, and Lo et al. (2000) further find that technical analysis adds value to investing in individual stocks beyond the index. Covering over 24,000 stocks spanning 22 years, Wilcox and Crittenden (2009) further continue to find profitability of technical analysis. Across various asset classes, Faber (2007) show 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 MAs and the gains are much larger than those for stock indices. Moreover, Gehrig and Menkhoff (2006) argue that technical analysis today 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 base 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 the MA can help to learn about the predictability and so to add value to asset allocation. Note that both the MA and the momentum strategies are trend-following. The more a trend is to continue, the more the profit the strategies may have. Hence, models that explain momentum profits can also help to understand the profitability of the MA. In the market underreaction story, for example, Barberis, Shleifer, and Vishny

(1998) argue 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 underreaction to public information by investors.

Explanations above help to understand why the MA strategy is profitable, the question is whether such profitability can be explained by compensation for risk. While this may well be the case, the alphas we found for the MA strategy 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.

III 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 strategy, and then consider the use of volatility decile portfolios formed from NYSE/Amex stocks or NYSE stocks as opposed to Nasdaq stocks, as well as the use of the value-weighted size decile portfolios. We analyze further the profitability of the MA timing strategy when transaction costs are imposed. Finally we examine the profitability in 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 leg 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 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 5.33% to 8.02% 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 20.39% per annum, which is about 4% less than that of the 10-day MA. In contrast, the 50-day MA timing strategy generates a risk-adjusted abnormal return that is about 31% less than that generated by the 10-day MA. In addition, the 200-day MA timing strategy only generates about 29% of the risk-adjusted abnormal return of the 10-day MA.

Second, similar to the 10-day MA timing strategy, all the other MA timing strategies generate monotonically increasing abnormal returns across the deciles, up to the highest decile which has slightly lower values than those of 9th decile. However, differences in the abnormal returns between the highest and lowest deciles decline as the lag length increases. For example, the abnormal return of the highest deciles is about 2.65 (20.39/7.69) times of the abnormal return of the lowest decile when $L = 20$, and only about 1.16 (6.19/5.33) times of that of the lowest decile when $L = 200$.

B Alternative Volatility Decile Portfolios

Since Nasdaq has many small stocks, it is of interest to see how the results would change if more larger stocks are used to form the decile portfolios. For this reason, we consider in this subsection the volatility decile portfolios formed from NYSE/Amex stocks.[6] Moreover, we also consider the volatility decile portfolios formed from NYSE stocks only since Amex has many small stocks too. As Fama-French factors are only available from July 1, 1963, we will conduct our analysis for the period from July 1, 1963 to December 31, 2009.

Table IV reports the average returns and Fama-French alphas, with the use of the NYSE/Amex volatility decile portfolios. The results are fundamentally similar to those using the Nasdaq volatility decile portfolios. The MAPs still have large positive average returns and large positive alphas, across all the deciles and all the lag lengths. In addition, both the average returns and the alphas increase monotonically from the first decile to the 9th decile, and then slightly decline for the highest volatility decile portfolio. Nevertheless, the highest volatility decile portfolio still outperforms the lowest volatility decile portfolio

[6] CRSP renamed this as NYSE/Alternext because the American Stock Exchange was acquired by NYSE Euronext and was renamed to NYSE Alternext. However, NYSE Euronext rebranded NYSE Alternext to NYSE Amex on Friday, March 6, 2009. Therefore we will continue to use NYSE/Amex.

by considerable amounts. Compared to the Nasdaq volatility decile portfolios, NYSE/Amex volatility decile portfolios generate slightly higher performance for the first two decile portfolios, but slightly lower performance for the rest of decile portfolios.

Table V reports the results for the NYSE volatility decile portfolios. Except the first decile, the results are very similar to earlier ones. For example, when $L = 10$, while the first decile alpha changes substantially from 9.83% in the NYSE/Amex case to 3.22%, the the second decile alpha changes only from 11.02% to 10.62%, and the third changes from 11.58% to 13.66%, even a higher value. Since NYSE is almost free of the small stocks problem, the large alphas we documented are unlikely be driven by small stocks. Overall, it is clear that the fundamental result of the profitability of the MA timing strategy is completely unaltered with the use of the alternative volatility decile portfolios.

C Value-Weighted Size Decile Portfolios

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

Table VI reports the average returns and Fama-French alphas for the MAPs based on the size portfolios formed from stocks traded on NYSE/Amex/Nasdaq.[7] The results are similar to those using the volatility decile portfolios, except the order is reversed. Both the average returns and Fama-French alphas decrease from low size deciles (small stocks) to high size deciles (large stocks). Similar to NYSE volatility decile portfolios, there is a large difference in performance between the highest size decile and the next highest decile (ninth decile). For example, the average returns are all close to zero and insignificant, and the abnormal returns (Fama-French alphas) are around 3% per annum for the highest size decile. However, the abnormal returns range from 5.95% in MAP(200) to 13.70% in MAP(10) for the second highest decile. Moreover, about half of the MAP(10) decile portfolios yield Fama-French alphas greater than 20% per annum, and more than half of the MAP(100) decile portfolios yield Fama-French alphas greater than 10% per annum. Clearly, the profitability of the MA

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

timing strategy remains strong even with the use of the value-weighted size decile portfolios.

D Average Holding Days, Turnover Rate and Transaction Costs

Since the MA timing strategy is based on daily signals, it is of interest to see how often it trades. If the turnover rate is hight, 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 turnover rates, as well as their returns after accounting for the trading costs.

The average holding days are reported in Table VII. It is interesting that longer lag length results in longer average holding days. For example, the 10-day MA timing strategy has about 11 average holding days, whereas the 200-day MA has average holding days ranging from 87 to 233 days. In addition, the differences in the holding days across the deciles also increase with the lag length, but the highest volatility deciles do not necessarily have the shortest or the longest holding days. To assess further on trading, we also estimate the fraction of days when the trades occur relative to all the days and report it as 'Turnover' in Table VII. Since longer lag length captures longer trends, the turnover is inversely related the lag length. For example, the 10-day MA strategy requires about 17% trading days, whereas the 200-day MA has about only 2%, 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, especially for the highest volatility decile portfolio. This is indeed the case as it turns out below.

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 1 basis point to 50 basis points. For example, Balduzzi and Lynch (1999) use 1 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. Following the latter, we set τ equal to 25 basis points, which amounts to 63% ($252 \times .25$) per annum trading costs if one trades every trading day.

Table VIII reports the abnormal returns of the MAPs under the transaction cost of 25 basis points per trade. The transaction cost has reduced the abnormal returns across the various MA timing strategies. The 10-day MA strategy experiences the largest impact. Its abnormal returns drop about 6 to 7% per annum on average due to its relatively high trading frequency. However, the 20-day MA experiences only about 3 to 4% per annum drop in abnormal performance, whereas the 200-day MA has only about 0.5 to 0.7% drop in the abnormal returns. Nevertheless, all of the MAPs still have significantly positive abnormal returns except the first two deciles of the 10-day MA timing strategy. Despite of the transaction costs, the 10-day MA timing strategy still generates greatly significant abnormal returns, 15.81% and 17.95%, for the highest decile and the 9th decile portfolios. Interestingly, though, after accounting for transaction costs, the 20-day MA timing strategy replaces the 10-day MA now as the best performer of all the MA timing strategies. It now yields the highest abnormal returns especially for the higher volatility decile portfolios, from the 4th decile up to the 10th decile, for instance. Overall, transaction costs have little impact on performance, and the MAPs still have economically highly significant abnormal returns.

E 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 equal time length.

Table IX 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 abnormal returns, similar to the case of the entire sample period. Moreover, both the CAMP and the Fama-French alphas increase monotonically across the deciles except for the highest decile which often has lower alphas than the 9th decile. Once again, the market betas are significantly negative, so are the SMB betas. In addition, the HML betas are largely insignificant and small, with the exception of the first four deciles 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 than in the entire sample period. This is especially apparent for the low volatility deciles. For example, the lowest volatility decile has a CAPM and Fama-French alpha of about 10.23% and 11.08 % per annum, respectively, in the first subperiod, but they reduce to 2.15% and 3.27% per annum, respectively, in the second subperiod, and compared to 6.17% and 7.47% in the entire sample period. However, for the high volatility deciles, the performance are quite similar in both of the subperiods. Overall, the results continue to support that the MAPs, especially those high decile ones, constitute a new anomaly in asset pricing.

IV Comparison with Momentum

In this section, we 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 and their sensitivities to default and liquidity risks.

A Business Cycles

With returns on the momentum factor (UMD) which is readily available from French's web site, we can compute the correlations between UMD and the MAPs, which range from 0.0375 to 0.1513 from the lowest Nasdaq decile MAP to the highest decile MAP. Because of the small and statistically insignificant correlations, there is little statistical relation between the MAPs and the UMD. This fact is also further verified that MAPs do not have any significant exposure to the UMD factor, i.e., their UMD betas are insignificantly different from zero. Hence, there is little statistical relation between the MAPs and the UMD even though both are trend-following. The question is whether there is any economic linkage between them.

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 are 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 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, Gutierrez, and Hameed (2004) argue that the momentum strategy is profitable only after the 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 et al. (2010) extend the results to the early periods of Victorian era.

In our comparison of the performance of both the UMD and the MAPs, we regress both the UMD factor and MAPs 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 et al. (2003) and Chabot et al. (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 are 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 5.57% to 21.46% per annum in expansionary periods and ranging from 16.31% to 42.81% 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 tells 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 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 et al. (2004), Huang (2006), and Chabot et al. (2010), the alpha of the UMD factor is insignificant, indicating that the momentum strategy has insignificant risk-adjusted abnormal returns in the down market, whereas the coefficient of the *Up Market* dummy is statistically significant and economically considerable, about 12.68% 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-reverting in the price that cannot be immediately captured by the MA timing strategy.

B Default Risk

Chordia and Shivakumar (2002) provide evidence that momentum profits can be explained by exposure to macroeconomic variables including default spread, defined as the yield spread between BAA and AAA corporate bonds. They show that when regressing the momentum returns on a number of macroeconomic variables, default spread has negative and significant coefficient. Avramov and Chordia (2006) also show that momentum profits are related to the default spread. Avramov, Chordia, Jostova, and Philipov (2007) further argue that there is a strong link between momentum and credit rating, and that the momentum profits are exclusively generated by low-grade firms and are nonexistent among high-grade firms. Their results suggest a positive relation between momentum profits and default spread.

Panel A of Table XI reports the results of regressing the UMD factor and the MAPs on the Fama-French three factors and the default spread. Consistent with Chordia and Shivakumar (2002), the coefficient of the UMD factor on the default spread is negative and significant. In contrast, the MAPs are insensitive to the default spread: all the coefficients are positive but insignificant. Hence, on an economic ground as measured by the default risk, the UMD and MAPs represent different risk exposures too.

C Liquidity Risk

Pástor and Stambaugh (2003) propose an aggregate liquidity measure and show that the spread portfolio which takes a long position on the highest quintile portfolio and a short position on the lowest quintile portfolio sorted on the aggregate liquidity can explain certain portion of the abnormal return of the UMD factor portfolio. However, Pástor and Stambaugh (2003) also point out that the liquidity beta of the UMD factor is positive but insignificant.

Sadka (2006) also show that momentum profits are related to liquidity risk premium.

Panel B of Table XI reports the results of regressing both the UMD factor and MAP portfolios on the Fama-French three factors and the aggregate liquidity measure of Pástor and Stambaugh (2003). The momentum strategy is insensitive to this aggregate liquidity measure, consistent with Pástor and Stambaugh (2003). On the other hand, the coefficients of the MAPs are all negative, and are statistically significant for the high volatility decile MAPs. In fact, the regression coefficients increase monotonically in magnitude across the deciles. Once again, from the liquidity point of view, the UMD and MAPs are different.

V Concluding Remarks

In this paper, we document that a standard use of the moving averages, a popular form of technical analysis, in investing portfolios sorted by volatility, generates 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 SML and HML factors. The abnormal returns, relative to the CAPM and the Fama and French (1993) three-factor models, are high as a result. For the high deciles, the abnormal returns are much higher than those from the momentum strategy which is about 12% annualized. The abnormal returns remain high even after accounting for transaction costs. While the moving average timing strategy is trend-following similar to the momentum strategy, its performance has little correlation with the momentum strategy, and behaves differently over business cycles, default and liquidity risks.

Our paper appears to provide a new research stimulus in two 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 those sorted by volatility. Given the vast literature on technical analysis, potentially many open questions may be explored and answered. Second, our study presents an exciting new anomaly in the anomaly 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. Because of its trend-following nature, various issues that have been investigated about the momentum can also be investigated about the moving average anomaly. 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 Nasdaq volatility decile portfolios as the investment assets. We report the average return and the standard deviation 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. The sample period is from January 2, 1973 to December 31, 2009.

Rank	Avg Return	Std Deviation	Avg Return	Std Deviation	Avg Return	Std Deviation
	Panel A		**Panel B**		**Panel C**	
	Volatility Decile Portfolios		**MA(10) Timing Portfolios**		**MAP**	
Low	14.91	7.75	20.06	5.06	5.17	5.83
2	16.36	9.87	22.09	6.46	5.78	7.43
3	17.15	11.88	26.02	7.62	8.92	9.05
4	16.53	13.38	27.87	8.51	11.37	10.24
5	18.74	15.04	32.69	9.68	14.03	11.39
6	19.15	16.36	35.94	10.49	16.87	12.40
7	19.57	17.10	38.59	10.89	19.09	13.00
8	24.34	17.88	45.46	11.73	21.23	13.26
9	29.86	18.67	51.38	12.26	21.61	13.81
High	70.62	20.65	89.12	15.31	18.55	13.41
Nasdaq	23.66	13.71				

Table II
CAPM and Fama-French Alphas

The table reports the alphas, betas and the adjusted R-Squares of the regressions of the MAPs on the market excess return (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% level and 5% level is given by an ** and an *, respectively. The sample period is from January 2, 1973 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	6.17**	-0.20**	31.79	7.48**	-0.25**	-0.19**	-0.16**	41.88
	(6.47)	(-11.49)		(8.05)	(-12.26)	(-9.56)	(-5.90)	
2	7.14**	-0.27**	36.20	8.62**	-0.33**	-0.28**	-0.15**	47.59
	(6.20)	(-13.26)		(7.80)	(-13.32)	(-11.16)	(-5.00)	
3	10.65**	-0.34**	40.10	12.24**	-0.41**	-0.36**	-0.15**	51.69
	(7.94)	(-15.71)		(9.67)	(-15.29)	(-13.24)	(-4.15)	
4	13.37**	-0.40**	41.87	14.74**	-0.46**	-0.41**	-0.10**	53.09
	(9.08)	(-17.24)		(10.74)	(-16.37)	(-15.49)	(-2.64)	
5	16.22**	-0.44**	40.60	17.38**	-0.50**	-0.48**	-0.04	53.11
	(10.09)	(-19.13)		(11.83)	(-17.86)	(-16.64)	(-1.06)	
6	19.24**	-0.47**	40.05	20.10**	-0.53**	-0.52**	0.01	52.68
	(10.99)	(-20.18)		(12.74)	(-18.57)	(-16.59)	(0.34)	
7	21.53**	-0.48**	38.46	22.53**	-0.55**	-0.56**	0.00	51.41
	(11.48)	(-19.47)		(13.49)	(-18.00)	(-16.13)	(0.04)	
8	23.59**	-0.47**	34.61	24.15**	-0.53**	-0.56**	0.07	47.75
	(11.58)	(-19.47)		(13.49)	(-18.66)	(-14.79)	(1.54)	
9	23.93**	-0.46**	30.90	24.44**	-0.52**	-0.56**	0.08	42.98
	(10.75)	(-17.58)		(12.39)	(-17.01)	(-12.37)	(1.62)	
High	20.56**	-0.40**	24.41	21.38**	-0.46**	-0.51**	0.02	34.51
	(9.04)	(-13.86)		(10.17)	(-13.28)	(-10.34)	(0.30)	

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. The results are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1% level and 5% level is given by an ** and an *, respectively. The sample period is from January 2, 1973 to December 31, 2009.

Rank	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α
	MAP(20)		**MAP(50)**		**MAP(100)**		**MAP(200)**	
Low	5.19**	7.69**	4.10**	6.84**	3.19**	6.15**	2.32*	5.33**
	(4.58)	(8.25)	(3.49)	(7.09)	(2.79)	(6.50)	(2.09)	(5.66)
2	5.41**	8.44**	3.98**	7.20**	2.81	6.45**	1.97	5.71**
	(3.77)	(7.50)	(2.70)	(6.09)	(1.95)	(5.60)	(1.41)	(4.98)
3	8.33**	11.84**	6.28**	10.10**	3.09	7.26**	1.93	6.36**
	(4.85)	(9.50)	(3.47)	(7.60)	(1.74)	(5.35)	(1.12)	(4.72)
4	10.93**	14.43**	7.61**	11.24**	4.06*	8.35**	1.67	6.03**
	(5.59)	(10.56)	(3.74)	(7.66)	(1.98)	(5.55)	(0.85)	(4.00)
5	12.53**	16.02**	8.54**	12.23**	3.98	8.24**	2.44	6.74**
	(5.66)	(10.65)	(3.69)	(7.65)	(1.72)	(4.95)	(1.08)	(3.96)
6	14.30**	17.74**	10.24**	13.95**	5.36*	9.74**	2.38	6.64**
	(5.94)	(10.72)	(4.04)	(7.91)	(2.10)	(5.30)	(0.96)	(3.49)
7	17.08**	20.72**	11.67**	15.51**	6.94*	11.34**	3.56	8.02**
	(6.65)	(11.69)	(4.36)	(8.23)	(2.57)	(5.72)	(1.34)	(3.93)
8	18.72**	21.70**	12.82**	15.92**	7.24*	10.75**	3.72	7.28**
	(6.95)	(11.52)	(4.55)	(7.86)	(2.52)	(4.95)	(1.31)	(3.25)
9	19.19**	22.09**	13.46**	16.53**	8.39**	11.60**	3.98	7.15**
	(6.82)	(10.81)	(4.60)	(7.57)	(2.79)	(4.97)	(1.31)	(2.90)
High	17.49**	20.39**	11.52**	14.65**	6.37*	9.55**	3.17	6.19*
	(6.30)	(9.34)	(4.00)	(6.26)	(2.20)	(3.91)	(1.13)	(2.47)

Table IV
NYSE/Amex Volatility 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 volatility 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% level and 5% level is given by 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)**	
Low	8.48**	9.83**	6.55**	7.93**	4.52**	5.89**	2.48*	3.76**	1.81	3.09**
	(9.28)	(12.32)	(7.10)	(9.71)	(4.59)	(6.68)	(2.53)	(4.17)	(1.87)	(3.46)
2	8.60**	11.02**	7.00**	9.50**	4.63**	7.23**	2.58*	5.24**	1.50	4.04**
	(7.08)	(11.43)	(5.72)	(9.75)	(3.64)	(7.10)	(2.03)	(5.09)	(1.21)	(3.93)
3	8.69**	11.58**	7.32**	10.30**	4.80**	7.97**	2.37	5.58**	1.92	5.05**
	(6.12)	(10.85)	(5.09)	(9.46)	(3.23)	(7.09)	(1.59)	(4.85)	(1.33)	(4.44)
4	9.88**	13.34**	7.57**	11.03**	5.15**	9.00**	2.95	6.99**	2.24	6.12**
	(6.18)	(11.43)	(4.59)	(9.02)	(3.07)	(7.26)	(1.75)	(5.58)	(1.38)	(4.89)
5	11.33**	15.45**	8.30**	12.47**	5.46**	9.96**	3.09	7.95**	1.44	6.18**
	(6.34)	(12.15)	(4.43)	(9.15)	(2.87)	(7.16)	(1.63)	(5.70)	(0.78)	(4.35)
6	12.49**	16.96**	9.82**	14.31**	6.20**	11.06**	3.95	9.12**	2.01	7.03**
	(6.46)	(12.56)	(4.87)	(10.05)	(3.00)	(7.45)	(1.92)	(6.14)	(1.00)	(4.65)
7	13.26**	18.00**	11.00**	15.74**	7.23**	12.36**	4.22	9.64**	2.06	7.44**
	(6.34)	(12.50)	(5.06)	(10.46)	(3.23)	(7.88)	(1.87)	(6.00)	(0.92)	(4.52)
8	17.02**	21.87**	14.19**	19.17**	9.52**	14.77**	5.77*	11.31**	2.58	7.97**
	(7.53)	(14.40)	(6.04)	(12.13)	(3.86)	(8.82)	(2.32)	(6.57)	(1.03)	(4.42)
9	19.00**	23.72**	15.71**	20.78**	10.56**	15.53**	5.59*	10.78**	2.44	7.68**
	(8.00)	(14.57)	(6.42)	(12.65)	(4.07)	(8.69)	(2.10)	(5.69)	(0.91)	(3.91)
High	15.92**	20.29**	13.65**	18.18**	8.52**	12.94**	2.96	7.08**	1.63	5.71**
	(6.87)	(11.79)	(5.72)	(10.42)	(3.42)	(6.99)	(1.18)	(3.54)	(0.66)	(2.77)

Table V
NYSE Volatility 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 volatility 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% level and 5% level is given by 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)**	
Low	0.53	3.22**	-0.99	1.93	-1.35	1.85	-0.16	3.16**	0.65	4.04**
	(0.32)	(2.77)	(-0.58)	(1.63)	(-0.79)	(1.55)	(-0.09)	(2.61)	(0.39)	(3.38)
2	6.73**	10.62**	4.42*	8.43**	2.91	7.12**	1.89	6.29**	1.37	5.81**
	(3.88)	(8.82)	(2.42)	(6.69)	(1.60)	(5.48)	(1.04)	(4.87)	(0.76)	(4.40)
3	9.22**	13.38**	6.50**	10.62**	4.43*	8.79**	2.56	7.10**	1.19	5.84**
	(5.18)	(10.86)	(3.56)	(8.24)	(2.38)	(6.57)	(1.38)	(5.33)	(0.65)	(4.32)
4	9.25**	13.66**	6.49**	10.91**	3.85*	8.38**	2.60	7.62**	1.21	6.17**
	(5.02)	(10.64)	(3.41)	(8.22)	(2.00)	(6.02)	(1.35)	(5.54)	(0.64)	(4.39)
5	10.07**	14.92**	7.94**	12.89**	5.09**	10.10**	3.12	8.58**	1.60	7.07**
	(5.37)	(11.42)	(4.20)	(9.73)	(2.62)	(7.20)	(1.62)	(6.18)	(0.85)	(5.02)
6	10.84**	15.73**	7.78**	12.79**	4.75*	9.86**	3.33	8.80**	2.12	7.36**
	(5.70)	(11.85)	(4.07)	(9.55)	(2.38)	(6.93)	(1.68)	(6.24)	(1.10)	(5.11)
7	11.37**	15.96**	8.89**	13.64**	6.52**	11.40**	4.49*	9.74**	2.31	7.45**
	(6.10)	(12.02)	(4.72)	(10.17)	(3.38)	(8.30)	(2.31)	(7.02)	(1.21)	(5.20)
8	12.09**	16.48**	8.87**	13.22**	6.63**	11.13**	4.56*	9.40**	2.38	7.08**
	(6.67)	(12.70)	(4.84)	(9.92)	(3.49)	(8.16)	(2.38)	(6.76)	(1.28)	(5.01)
9	13.81**	17.85**	10.93**	15.10**	8.37**	12.57**	5.38**	9.78**	2.88	7.20**
	(7.78)	(13.90)	(6.06)	(11.46)	(4.55)	(9.31)	(2.85)	(6.96)	(1.54)	(5.02)
High	15.12**	18.81**	12.62**	16.37**	9.00**	12.67**	5.00*	8.71**	1.65	5.40**
	(8.24)	(13.62)	(6.73)	(11.59)	(4.67)	(8.72)	(2.50)	(5.66)	(0.82)	(3.42)

Table VI
NYSE/Amex/Nasdaq Value-Weighted 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% level and 5% level is given by 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)**	
Low	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)
2	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)
3	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)
4	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)
5	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)
6	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)
7	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)
8	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)
9	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)
High	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)

Table VII
Average Holding Days and Turnover Rates

The table reports the average consecutive holding days (Holding) and fraction of trading days (Turnover) of the MAPs when they are constructed with 10 Nasdaq volatility decile portfolios by using 10-, 20-, 50-, 100- and 200-day moving average prices, respectively. The sample period is from January 2, 1973 to December 31, 2009.

Rank	Holding	Turnover	Holding	Turnover	Holding	Turnover	Holding	Turnover	Holding	Turnover
	MA(10)		**MA(20)**		**MA(50)**		**MA(100)**		**MA(200)**	
Low	15.83	0.13	28.68	0.07	66.91	0.03	114.78	0.02	176.93	0.01
2	12.24	0.16	20.75	0.10	44.43	0.05	74.68	0.03	138.81	0.01
3	11.77	0.17	21.41	0.09	42.78	0.05	66.72	0.03	101.23	0.02
4	11.06	0.18	19.44	0.10	38.65	0.05	69.34	0.03	129.82	0.02
5	11.38	0.18	19.32	0.10	41.24	0.05	64.16	0.03	87.16	0.02
6	11.45	0.17	19.72	0.10	41.88	0.05	65.22	0.03	112.97	0.02
7	11.28	0.18	19.12	0.10	39.95	0.05	67.32	0.03	91.39	0.02
8	11.69	0.17	20.44	0.10	50.18	0.04	65.84	0.03	131.42	0.02
9	12.38	0.16	21.21	0.09	44.75	0.04	91.69	0.02	165.09	0.01
High	14.43	0.14	25.97	0.08	56.03	0.04	98.59	0.02	233.22	0.01

Table VIII
Transaction Costs

The table reports the average returns (Avg Ret) and the Fama-French alphas (FF α) of the MAPs when they are constructed with 10 Nasdaq volatility decile portfolios by using 10-, 20-, 50-, 100- and 200-day moving average prices, respectively. The results account for a transaction cost of 25 basis points for each trade in the decile portfolios, and are annualized in percentage points. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1% level and 5% level is given by an ** and an *, respectively. The sample period is from January 2, 1973 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
Transaction Cost $\tau = 25$ bps										
	MAP(10)		**MAP(20)**		**MAP(50)**		**MAP(100)**		**MAP(200)**	
Low	-0.94	1.39	1.63	4.12**	2.31	5.03**	2.19	5.14**	1.88	4.88**
	(-0.78)	(1.34)	(1.37)	(4.08)	(1.92)	(4.96)	(1.90)	(5.33)	(1.68)	(5.13)
2	-1.10	1.73	1.24	4.26**	1.86	5.09**	1.76	5.39**	1.34	5.06**
	(-0.73)	(1.41)	(0.83)	(3.51)	(1.24)	(4.11)	(1.21)	(4.59)	(0.95)	(4.37)
3	1.89	5.21**	4.15*	7.66**	4.47*	8.27**	1.70	5.88**	1.17	5.58**
	(1.04)	(3.76)	(2.35)	(5.76)	(2.44)	(6.04)	(0.95)	(4.25)	(0.68)	(4.10)
4	4.36*	7.74**	6.70**	10.20**	5.49**	9.12**	2.76	7.06**	0.64	5.00**
	(2.17)	(5.21)	(3.35)	(7.05)	(2.67)	(6.04)	(1.34)	(4.62)	(0.32)	(3.27)
5	7.13**	10.49**	8.44**	11.91**	6.50**	10.19**	2.67	6.93**	1.61	5.90**
	(3.23)	(6.64)	(3.73)	(7.53)	(2.78)	(6.20)	(1.15)	(4.11)	(0.71)	(3.44)
6	9.98**	13.21**	10.14**	13.57**	8.24**	11.95**	4.05	8.43**	1.33	5.60**
	(4.18)	(7.86)	(4.13)	(7.83)	(3.23)	(6.63)	(1.58)	(4.53)	(0.53)	(2.92)
7	12.11**	15.55**	13.03**	16.68**	9.57**	13.40**	5.78*	10.18**	2.88	7.33**
	(4.81)	(8.73)	(4.98)	(9.03)	(3.55)	(6.98)	(2.13)	(5.09)	(1.08)	(3.58)
8	14.56**	17.48**	14.93**	17.91**	10.92**	14.02**	6.01*	9.52**	2.83	6.39**
	(5.52)	(9.23)	(5.46)	(9.19)	(3.85)	(6.82)	(2.09)	(4.34)	(1.00)	(2.84)
9	15.13**	17.95**	15.26**	18.17**	11.62**	14.68**	7.27*	10.48**	3.34	6.50**
	(5.41)	(8.67)	(5.33)	(8.60)	(3.94)	(6.63)	(2.41)	(4.46)	(1.10)	(2.62)
High	13.00**	15.81**	14.36**	17.26**	10.15**	13.27**	5.57	8.76**	2.62	5.63*
	(4.81)	(7.23)	(5.10)	(7.72)	(3.51)	(5.61)	(1.92)	(3.57)	(0.93)	(2.24)

Table IX
Subperiods

The table reports the alphas, betas and the adjusted R-squares of the regressions of the MAPs on the market excess return and on the Fama-French three factors, respectively, over two equally divided subperiods: from January 2, 1973 to June 30, 1991 (Panel A) and from July 1, 1991 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% level and 5% level is given by an ** and an *, respectively.

Panel A: Period Jan 02, 1973 - June 30, 1991								
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	10.23**	-0.12**	23.12	11.08**	-0.20**	-0.24**	-0.06**	45.35
	(8.70)	(-5.55)		(10.37)	(-6.00)	(-6.43)	(-2.92)	
2	13.51**	-0.19**	27.33	14.56**	-0.30**	-0.37**	-0.06*	51.55
	(8.79)	(-6.24)		(10.82)	(-6.41)	(-6.88)	(-2.04)	
3	15.94**	-0.23**	29.97	17.05**	-0.36**	-0.44**	-0.05	54.30
	(9.23)	(-7.21)		(11.55)	(-7.31)	(-7.77)	(-1.66)	
4	17.74**	-0.27**	31.00	18.67**	-0.41**	-0.50**	-0.01	55.32
	(9.17)	(-7.84)		(11.41)	(-7.91)	(-9.71)	(-0.26)	
5	19.95**	-0.31**	31.61	20.75**	-0.46**	-0.58**	0.03	57.55
	(9.67)	(-9.92)		(12.38)	(-9.81)	(-11.28)	(0.76)	
6	20.40**	-0.34**	31.35	21.09**	-0.49**	-0.63**	0.06	57.10
	(9.12)	(-11.38)		(11.57)	(-10.95)	(-11.83)	(1.48)	
7	22.34**	-0.37**	32.18	23.19**	-0.53**	-0.67**	0.04	57.30
	(9.49)	(-10.41)		(12.02)	(-10.02)	(-12.23)	(0.93)	
8	22.63**	-0.36**	29.43	23.40**	-0.52**	-0.67**	0.05	54.44
	(9.21)	(-11.03)		(11.43)	(-10.62)	(-12.93)	(1.16)	
9	23.55**	-0.38**	27.28	24.69**	-0.56**	-0.73**	0.02	50.94
	(8.69)	(-10.55)		(10.86)	(-10.51)	(-11.73)	(0.30)	
High	21.62**	-0.35**	22.23	22.74**	-0.53**	-0.71**	0.01	43.95
	(7.70)	(-9.34)		(9.15)	(-9.63)	(-11.38)	(0.27)	

	Panel B: Period July 01, 1991 - 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	2.15	-0.25**	37.75	3.27*	-0.27**	-0.13**	-0.16**	43.48
	(1.43)	(-10.36)		(2.24)	(-10.87)	(-6.61)	(-5.39)	
2	0.81	-0.32**	41.91	2.10	-0.34**	-0.21**	-0.16**	48.17
	(0.47)	(-11.76)		(1.25)	(-11.85)	(-10.14)	(-4.68)	
3	5.42**	-0.41**	46.61	6.77**	-0.44**	-0.28**	-0.15**	52.54
	(2.64)	(-14.26)		(3.43)	(-13.80)	(-11.53)	(-3.67)	
4	9.07**	-0.47**	48.74	10.18**	-0.50**	-0.32**	-0.09*	54.06
	(4.08)	(-15.84)		(4.77)	(-14.84)	(-12.31)	(-2.18)	
5	12.57**	-0.51**	46.34	13.49**	-0.53**	-0.39**	-0.04	52.85
	(5.10)	(-16.79)		(5.78)	(-15.65)	(-12.54)	(-0.73)	
6	18.15**	-0.55**	45.58	18.74**	-0.57**	-0.42**	0.03	52.38
	(6.76)	(-17.40)		(7.50)	(-16.00)	(-11.78)	(0.66)	
7	20.78**	-0.55**	42.56	21.57**	-0.57**	-0.47**	0.01	50.04
	(7.13)	(-16.28)		(8.05)	(-15.35)	(-10.89)	(0.24)	
8	24.61**	-0.54**	38.07	24.92**	-0.54**	-0.47**	0.10	46.11
	(7.60)	(-15.79)		(8.51)	(-15.64)	(-9.39)	(1.71)	
9	24.36**	-0.51**	33.24	24.58**	-0.52**	-0.45**	0.11	40.56
	(6.90)	(-13.82)		(7.62)	(-13.92)	(-7.69)	(1.78)	
High	19.53**	-0.43**	25.76	20.15**	-0.44**	-0.39**	0.02	31.27
	(5.45)	(-10.56)		(5.93)	(-10.34)	(-6.19)	(0.28)	

Table X
Business Cycles and Up Markets

Panel A of the table reports the regression results of the Nasdaq MAPs 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 three-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% level and 5% level is given by an ** and an *, respectively. The sample period in both panels is from January 2, 1973 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	5.57**	-0.24**	-0.19**	-0.15**	10.74**	42.08	7.96**	-0.25**	-0.19**	-0.16**	-0.65	41.88
	(6.49)	(-12.28)	(-9.57)	(-5.93)	(3.53)		(4.79)	(-12.26)	(-9.57)	(-5.90)	(-0.35)	
2	6.22**	-0.33**	-0.28**	-0.15**	13.47**	47.78	12.23**	-0.33**	-0.28**	-0.15**	-4.95*	47.62
	(6.09)	(-13.33)	(-11.17)	(-5.02)	(3.54)		(5.93)	(-13.33)	(-11.19)	(-5.00)	(-2.16)	
3	9.96**	-0.41**	-0.36**	-0.15**	12.80**	51.80	15.85**	-0.41**	-0.36**	-0.15**	-4.95	51.70
	(8.58)	(-15.33)	(-13.25)	(-4.17)	(2.95)		(6.43)	(-15.30)	(-13.27)	(-4.16)	(-1.82)	
4	12.08**	-0.46**	-0.41**	-0.10**	14.99**	53.21	18.06**	-0.46**	-0.41**	-0.10**	-4.55	53.10
	(9.28)	(-16.41)	(-15.52)	(-2.65)	(3.34)		(6.77)	(-16.37)	(-15.52)	(-2.64)	(-1.54)	
5	15.19**	-0.50**	-0.48**	-0.04	12.30**	53.17	22.15**	-0.50**	-0.48**	-0.04	-6.54*	53.13
	(10.96)	(-17.90)	(-16.65)	(-1.06)	(2.45)		(7.83)	(-17.88)	(-16.67)	(-1.06)	(-2.07)	
6	17.66**	-0.53**	-0.52**	0.02	13.72**	52.75	25.49**	-0.53**	-0.52**	0.01	-7.38*	52.70
	(11.64)	(-18.61)	(-16.61)	(0.34)	(2.61)		(7.86)	(-18.59)	(-16.62)	(0.34)	(-2.06)	
7	19.89**	-0.55**	-0.56**	0.00	14.84**	51.48	27.82**	-0.55**	-0.56**	0.00	-7.25*	51.43
	(12.06)	(-18.04)	(-16.14)	(0.04)	(2.79)		(8.12)	(-18.01)	(-16.15)	(0.04)	(-1.92)	
8	21.46**	-0.53**	-0.56**	0.07	15.11**	47.82	29.58**	-0.53**	-0.56**	0.07	-7.44	47.77
	(12.07)	(-18.70)	(-14.79)	(1.55)	(2.60)		(7.65)	(-18.67)	(-14.81)	(1.54)	(-1.76)	
9	20.47**	-0.52**	-0.56**	0.08	22.34**	43.13	31.81**	-0.52**	-0.56**	0.08	-10.09*	43.02
	(10.21)	(-17.04)	(-12.37)	(1.63)	(3.67)		(7.81)	(-17.02)	(-12.39)	(1.62)	(-2.23)	
High	17.34**	-0.46**	-0.51**	0.02	22.68**	34.67	25.98**	-0.46**	-0.51**	0.02	-6.31	34.52
	(8.10)	(-13.29)	(-10.34)	(0.31)	(3.53)		(7.19)	(-13.29)	(-10.36)	(0.30)	(-1.49)	
UMD	13.02**	-0.20**	-0.03	-0.45**	-8.77	11.80	2.20	-0.20**	-0.03	-0.45**	12.67*	11.85
	(5.55)	(-6.19)	(-0.81)	(-7.05)	(-1.06)		(0.39)	(-6.19)	(-0.78)	(-7.04)	(2.07)	

Table XI
Default and Liquidity Risks

Panel A of the table reports the regression results of the Nasdaq MAPs on the Fama-French market portfolio, SMB and HML factors, and a default risk measure (Def Spd), which is the yield difference between BAA and AAA corporate bonds. It also reports the same regression with the momentum factor, UMD, as the dependent variable. Panel B of the table reports similar regression results when the liquidity factor (PSInnov) of Pástor and Stambaugh (2003) is used. The intercepts are annualized and in percentage; the coefficients on either Def Spd or PSInnov are annualized. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1% level and 5% level is given by an ** and an *, respectively. The sample period in Panel A is from January 2, 1973 to December 31, 2009 and that in Panel B is from January 2, 1973 to December 31, 2008.

Decile	α	β_{mkt}	β_{smb}	β_{hml}	Def Spd	Adj. R^2	α	β_{mkt}	β_{smb}	β_{hml}	PSInnov	Adj. R^2
	Panel A: With Default Spread						**Panel B: With Liquidity**					
Low	4.96	-0.25**	-0.19**	-0.16**	0.02	41.89	7.78**	-0.26**	-0.20**	-0.18**	-0.19	42.96
	(1.50)	(-12.27)	(-9.56)	(-5.92)	(0.70)		(8.51)	(-11.51)	(-9.70)	(-6.23)	(-0.59)	
2	5.42	-0.33**	-0.28**	-0.15**	0.03	47.60	8.94**	-0.35**	-0.30**	-0.20**	-0.28	49.58
	(1.38)	(-13.33)	(-11.17)	(-5.01)	(0.75)		(8.13)	(-13.00)	(-11.48)	(-6.00)	(-0.71)	
3	6.45	-0.41**	-0.36**	-0.15**	0.05	51.71	12.33**	-0.43**	-0.38**	-0.20**	-0.46	53.73
	(1.36)	(-15.33)	(-13.26)	(-4.17)	(1.11)		(9.92)	(-15.12)	(-13.95)	(-5.25)	(-1.20)	
4	8.36	-0.46**	-0.41**	-0.10**	0.06	53.11	14.96**	-0.49**	-0.44**	-0.15**	-0.58	55.15
	(1.77)	(-16.41)	(-15.50)	(-2.65)	(1.25)		(11.02)	(-16.25)	(-16.55)	(-3.84)	(-1.44)	
5	12.71*	-0.50**	-0.48**	-0.04	0.04	53.12	17.82**	-0.53**	-0.52**	-0.10*	-0.60	55.16
	(2.32)	(-17.89)	(-16.64)	(-1.06)	(0.80)		(12.28)	(-18.11)	(-17.90)	(-2.26)	(-1.51)	
6	14.86**	-0.53**	-0.52**	0.02	0.05	52.69	20.53**	-0.56**	-0.56**	-0.04	-0.80*	54.76
	(2.79)	(-18.60)	(-16.61)	(0.34)	(0.93)		(13.13)	(-18.73)	(-18.04)	(-0.94)	(-1.93)	
7	14.57**	-0.55**	-0.56**	0.00	0.07	51.43	22.63**	-0.57**	-0.59**	-0.04	-1.20**	53.03
	(2.75)	(-18.05)	(-16.15)	(0.04)	(1.43)		(13.74)	(-17.58)	(-17.08)	(-0.80)	(-2.86)	
8	18.84**	-0.53**	-0.56**	0.07	0.05	47.76	24.36**	-0.54**	-0.59**	0.05	-1.37**	49.20
	(3.53)	(-18.69)	(-14.80)	(1.54)	(0.98)		(13.86)	(-18.77)	(-15.52)	(1.03)	(-3.14)	
9	16.22**	-0.52**	-0.56**	0.08	0.07	43.00	24.48**	-0.53**	-0.59**	0.06	-1.36**	44.24
	(2.84)	(-17.05)	(-12.38)	(1.62)	(1.43)		(12.52)	(-16.75)	(-12.89)	(1.10)	(-2.65)	
High	12.02	-0.46**	-0.51**	0.02	0.08	34.54	21.95**	-0.49**	-0.55**	-0.05	-1.76**	36.40
	(1.90)	(-13.31)	(-10.36)	(0.31)	(1.47)		(10.46)	(-13.24)	(-10.92)	(-0.77)	(-3.16)	
UMD	30.58**	-0.20**	-0.03	-0.45**	-0.17*	11.96	12.13**	-0.12**	0.01	-0.29**	-0.40	4.56
	(3.94)	(-6.20)	(-0.77)	(-7.05)	(-2.42)		(5.35)	(-3.40)	(0.22)	(-4.01)	(-0.64)	