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

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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 substantially outperform the buy-and-hold strategy. For high-volatility portfolios, the abnormal returns, relative to the capital asset pricing model (CAPM) and the Fama-French 3-factor models, are of great economic significance, and are greater than those from the well-known momentum strategy. Moreover, they cannot be explained by market timing ability, investor sentiment, default, and liquidity risks. Similar results also hold if the portfolios are sorted based on other proxies of information uncertainty.

I. Introduction

Technical analysis uses past prices and perhaps other past data to predict future market movements, of which momentum, high-frequency, and algorithm trading are social cases. In practice, all major brokerage firms publish technical commentaries on the markets, 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), Covel (2005), and Lo and Hasanhodzic (2009)), and it is one of the major information variables used for modern quantitative portfolio management (see, e.g., Chincarini and Kim (2006)). Empirical studies on whether

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technical analysis is profitable or not focus on daily and monthly signals, going back as far as Cowles (1933), who finds 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 using a moving average (MA) scheme, to forecast the market. More recently, Neely, Rapach, Tu, and Zhou (2013) find that using technical indicators is as good as using popular macroeconomic variables in forecasting the stock market, and Goh, Jiang, Tu, and Zhou (2013) show that technical analysis can even yield much better forecasts than the macroeconomic variables in the bond market. 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. While Neely et al. summarize various theoretical arguments for the use of technical analysis, Zhou and Zhu (2013) provide an equilibrium model that rationalizes directly the predictive value of the MAs.

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 portfolios sorted by volatility or other characteristics of the stocks that reflect information uncertainty. There are two intuitive reasons that motivate our examination of these decile portfolios. First, we view technical analysis as one of the signals investors use to make trading decisions. When information about stocks is very uncertain, fundamental 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, they are likely to show up more strongly for the high-information-uncertain stocks than for the low-information-uncertain stocks. Second, our use of technical analysis focuses on applying the popular technical tool, MAs, to time investments. This is a trend-following strategy (TFS), 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 underreaction to public information by investors, and investors will underreact even more in case of greater information uncertainty.

Our study will be focused on portfolios sorted by volatility. This is because stock volatility is a simple proxy of information uncertainty. The more uncertain the future information about a stock is, the more volatile the stock price is. The volatility-sorted portfolios are also of interest from the theoretical perspectives about technical analysis. Rational 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. However, we do examine other portfolios sorted based on size, distance to default, credit rating, analyst forecast dispersion, and earnings volatility, characteristics related to information uncertainty. Similar results hold. Our study points out that the profitability of the technical analysis depends on both asset characteristics (e.g., information uncertainty) and the value of technical analysis itself. In general, the more noise-to-signal ratio or the more uncertain the information, the more profitable the technical analysis.

For our major results, we apply the MA timing strategy to the Center for Research in Security Prices (CRSP) NYSE/AMEX volatility decile portfolios by computing the 10-day average prices of the decile portfolios (MA price). 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 T-bill) otherwise. Similar to the existing studies using the market indices, 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 for the highest decile), ranging from 8.42% per annum to 18.70% per annum. Moreover, the capital asset pricing model (CAPM) risk-adjusted returns, or the abnormal returns, are also increasing with the volatility deciles (except for the highest decile), ranging from 9.31% per annum to 21.76% per annum. Similarly, the Fama-French (1993) risk-adjusted returns also vary monotonically (except for the highest decile) from 9.80% per annum to 23.54% per annum.[1]

How robust are the results? We address this question in three ways. First, we consider alternative lag lengths of $L=20$, 50, 100, and 200 days for the MAs. 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 apply the same MA timing strategy to the commonly used CRSP value-weighted size decile portfolios from NYSE/AMEX/NASDAQ, which are proxies of the value-weighted 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 (1993) model range from 13.27% to 22.06% per annum.[2] Finally, we examine the trading behavior and break-even transaction cost (BETC). It turns out that the MA timing strategy does not trade very often and thus the BETC is reasonably large.

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 (Jegadeesh and Titman (1993)) appears to be the only one that is persistent and has survived since its publication. The momentum anomaly is about the empirical evidence that stocks that perform the best (worst) over a 3- to 12-month period tend to continue to perform well (poorly) over the subsequent 3–12 months. Comparing the momentum with the MAPs, the momentum anomaly earns roughly 12% annually, substantially less 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

[1] We choose the readily available CRSP decile portfolios as the investment assets to facilitate external replication. Similar results also obtain with CRSP NYSE or NASDAQ volatility decile portfolios.

[2] We also show that the profitability of the MA timing strategy is not directly related to the size anomaly, which is nonexistent in the most recent period, but the MAPs are still highly profitable for the medium-size to small decile portfolios.

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 they generate much higher abnormal returns in recessions. In contrast, the momentum strategy generates much lower 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.

To understand further the abnormal returns on the MAPs, we address three more questions. First, we analyze whether the strategy has any ability in timing the market, and whether there are 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 the Fung and Hsieh (2001) trend-following factor (TFF) formed on lookback straddles, and we find that the abnormal returns remain abnormal. Third, we investigate whether the abnormal returns can be explained by a conditional version of the Fama-French (1993) model (see, e.g., Ferson and Schadt (1996)). Unlike the anomalies analyzed by Stambaugh, Yu, and Yuan (2012), who find that many anomalies are sensitive to investor sentiment, we find that returns on the MAPs are not sensitive at all to changes in investor sentiment. We also find that the MAPs are insensitive to the Pástor and Stambaugh (2003) liquidity factor, but they 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.

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 MA timing strategy to the momentum strategy. Section VI analyzes the source of the profitability with the market timing models, the TFF, and conditional Fama-French (1993) models with macroeconomic variables. Section VII provides concluding remarks.

II. The Moving Average Timing Strategies

We use the set of 10 volatility decile portfolios as the underlying assets for the technical analysis. Daily index levels (prices) and returns of all the decile portfolios are readily available from the CRSP. More specifically, the decile portfolios are constructed based on the NYSE/AMEX stocks sorted into 10 groups (deciles) by their annual standard deviations estimated using the daily returns within the prior year. 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 sample period for

[3]Since value weighting is of interest but CRSP does not have it for the volatility decile portfolios, we analyze value-weighted size decile portfolios below.

the volatility decile portfolios is from July 1, 1963, to Dec. 31, 2009, to coincide with the Fama-French (1993) factors.

Denote by R_{jt} ($j = 1, \ldots, 10$) the returns on the volatility decile portfolios, and by P_{jt} ($j = 1, \ldots, 10$) the corresponding portfolio prices (index levels). The MA at day t of lag L is defined 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 including day t. Following, for example, Brock et al. (1992), we consider 10-, 20-, 50-, 100-, and 200-day MAs in this paper. The MA indicator is the most popular strategy of using technical analysis and is the 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 T-bill. So the MA provides an investment timing signal with a lag of 1 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 factors known and unknown to the investor. However, when the trend is broken, new factors may come into play, and the investor should then sell the asset. The 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 jth volatility decile portfolio on day t, and r_{ft} is the return on the risk-free asset, the 30-day T-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 indicates the profitability of the MA investment timing strategy.

III. Profitability of the Moving Average Portfolios

In this section, we provide 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 1 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, $\text{MAP}_{jt,10}$. Panel A provides the average return, the standard deviation, the skewness, and the Sharpe ratio of the buy-and-hold strategy across the 10 volatility deciles. The average 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.[4] The last row in the table provides the difference between the highest and the lowest deciles. For the decile portfolios, the difference is 33.98% per annum, both statistically and economically highly significant. 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.[5] 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 for the lowest decile is 4.16% versus 6.82%, and for the highest decile it is 14.41% versus 20.29%. In general, the MA timing strategy yields only about 65% of the 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" side of the market, that is, 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

[4]While Ang, Hodrick, Xing, and Zhang (2006) document a negative relation between 1-month lagged idiosyncratic volatility and future returns, Han and Lesmond (2011) argue that the negative relation is due to liquidity bias (bid-ask bounce) in the estimation of idiosyncratic volatility.

[5]To put this 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.

TABLE 1

Summary Statistics

We calculate the 10-day moving average (MA) prices each day using the last 10 days' closing prices including the current closing price, and compare the MA price with the current price as the timing signal. If the current price is above the MA 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 T-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 MA timing decile portfolios (Panel B), and the MA 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 percentages. We also report the annualized Sharpe ratio (SRatio) for the buy-and-hold portfolios and the MA timing portfolios, and we report the success rate for the MAPs. The sample period is from July 1, 1963, to Dec. 31, 2009; *t*-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively.

	Panel A. Volatility Decile Portfolios				*Panel B. MA(10) Timing Portfolios*				*Panel C. MAP*			
Rank	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	Success
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
	(10 80)				(31.47)				(10.79)			
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
	(9 22)				(25.03)				(7.98)			
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
	(8 53)				(21.73)				(6.80)			
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
	(7 81)				(20 31)				(6.80)			
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
	(7.17)				(19.48)				(6.94)			
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
	(7.08)				(19 62)				(7.10)			
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
	(6 56)				(18 55)				(6.96)			
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
	(5 86)				(18 98)				(8.30)			
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
	(6.59)				(20 29)				(8.91)			
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
	(15.03)				(28 61)				(7.62)			
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
	(13 51)				(21.09)				(4.22)			

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 CAPM regression of the zero-cost portfolio returns on the market portfolio,

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

where $r_{\text{MKT},t}$ is the daily excess return on the market portfolio. Panel A of Table 2 reports the results of the daily CAPM regressions of the MAPs formed with a 10-day MA timing strategy.[6] The alphas or risk-adjusted returns are even greater

[6]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%,

TABLE 2

CAPM and Fama-French Alphas

Table 2 reports the alphas, betas, and adjusted R^2s of the regressions of the MAPs fo med from the 10-day MA timing strategy on the market factor (Panel A) and on the Fama-French (1993) 3 factors (Panel B), respectively. The alphas are annualized and in percentages; the Newey and West (1987) robust t-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively. The sample period is from July 1, 1963, to Dec. 31, 2009.

	Panel A. CAPM			*Panel B. Fama-French*				
Rank	α	β_{MKT}	Adj. R^2 (%)	α	β_{MKT}	β_{SMB}	β_{HML}	Adj. R^2 (%)
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)	

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,[7] 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.

The large risk-adjusted abnormal returns clearly demonstrate the profitability of the MA timing strategy. The alphas are higher than the average returns because the MAPs have negative market betas. As shown in Panel A of Table 2, the market betas for the MAPs decrease from −0.18 to −0.61 across the volatility deciles. 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;

14.15%, 15.59%, 16.64%, 20.80%, 22.93%, and 19.26% with monthly regressions. We also include lagged market factors in the daily regression to deal with stale prices and obtain virtually the same results.

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

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) 3-factor model,

$$\text{(5)} \quad \mathrm{MAP}_{jt,L} = \alpha_j + \beta_{j,\mathrm{MKT}} r_{\mathrm{MKT},t} + \beta_{j,\mathrm{SMB}} r_{\mathrm{SMB},t} + \beta_{j,\mathrm{HML}} r_{\mathrm{HML},t} + \epsilon_{jt}, \quad j = 1, \ldots, 10,$$

where $r_{\mathrm{MKT},t}$, $r_{\mathrm{SMB},t}$, and $r_{\mathrm{HML},t}$ are the daily market excess return, daily return on the small-minus-big (SMB) factor, and daily return on the high-minus-low (HML) factor, respectively. Panel B of Table 2 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 magnitudes of the betas are smaller than those of the market betas. 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 3-factor model does have better explanatory power than the CAPM, evidenced by higher adjusted R^2s, and the improvement increases with the deciles.

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. The answer lies in the predictability of the market.

In earlier studies of stock price movements in the 1970s, 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 Ferson and Harvey (1991), find that various economic variables can forecast stock returns. Recent studies, such as Ang and Bekaert (2007), Campbell and Thompson (2008), Cochrane (2008), Rapach, Strauss, and Zhou (2010), (2013), and Hjalmarsson (2010), provide further evidence on return predictability. Many recent theoretical models allow for predictability as well (see, e.g., Cochrane 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 signal 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. Neely et al. (2013) provide the most recent evidence on the value of technical analysis in forecasting the 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) and Cespa and Vives (2012) 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 investors to learn about 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 investors to understand the profitability of the MA indicators. In the market underreaction 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 underreaction to public information by investors. However, none of the above models provides a direct link of the MAs to future stock returns, which was recently done by Zhou and Zhu (2013).

Explanations above help investors 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)), such magnitude of abnormal returns is unlikely to be 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.

D. Other Decile Portfolios

In this subsection, we investigate the dependence of the superior performance of the MA timing strategy on information uncertainty by considering four alternative decile portfolios. The first two are decile portfolios formed, following Avramov, Chordia, Jostova, and Philipov (2009), on the distance to default measure (Bharath and Shumway (2008)) and the credit rating, respectively. Both are measures of the likelihood to default and are related to information uncertainty. The last two decile portfolios are formed based on sorting stocks by the analyst forecast dispersion and income volatility. Both are used in the literature as proxies of information uncertainty (see, e.g., Diether, Malloy, and Scherbina (2002), Zhang (2006), and Berkman, Dimitrov, Jain, Koch, and Tice (2009)). All four sets of decile portfolios are equal weighted. The first three are rebalanced monthly, and the last is rebalanced quarterly.

To each of the four sets of alternative portfolios, we apply the same MA timing strategy and construct similar MAPs as we do for the volatility portfolios. Table 3 reports the performance of the MAPs of the alternative decile portfolios in terms of the average returns and the Fama-French (1993) alphas. The MAPs based on the distance to default decile portfolios (Panel A) generate both economically and statistically significant (risk-adjusted) abnormal returns. In fact, the alphas, though smaller than in the volatility portfolio case, are at very high levels compared with existing anomalies in finance. Moreover, the abnormal returns increase monotonically across the decile portfolios as the default risk increases, reaching the highest level at decile 7, then decrease somewhat over the remaining deciles, and finally drop significantly for the decile with the shortest distance to default or the highest default risk (High). The precipitous drop of the abnormal returns observed for the decile with the highest default risk may be because those firms are in great distress with trendless depressed prices for which the MA timing does

TABLE 3

Alternative Decile Portfolios

Table 3 reports the average returns (Avg Ret) and the Fama-French (1993) alphas (FF α) of the MAPs when they are constructed with 10 decile portfolios fo med from NYSE/AMEX/NASDAQ stocks by sorting the stocks on various variables that are related to info mation uncertainty. Panel A is the decile portfolios sorted on the distance-to-default measure (Bharath and Shumway (2008)); Panel B is the decile portfolios sorted on the credit rating. Both decile portfolios are reported by increasing default risk. Panel C is the decile portfolios sorted on the analyst forecast dispersion, and Panel D is the decile portfolios sorted on the income volatility. All decile portfolios are equal weighted. The returns are annualized and in percentages. The Newey and West (1987) robust *t*-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively. The starting date is Jan. 1, 1970; July 1, 1971; Jan. 1, 1971; and Jan. 1, 1981, respectively, for the 4 decile portfolios. All sample periods end by Dec. 31, 2009.

	Panel A. Distance to Default		*Panel B. Credit Rating*		*Panel C. Analyst Dispersion*		*Panel D. Income Volatility*	
Rank	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α
Low	5 59**	8.58**	−2.47	0.43	−1.78	1 84	4.37**	7.83**
	(3.18)	(7.36)	(−0.71)	(0.16)	(−0.77)	(1.11)	(2.61)	(6.30)
2	5 99**	8.68**	−3.19	0.52	1.61	6.11**	4.17*	8.22**
	(3 22)	(7.01)	(−0.80)	(0.20)	(0.70)	(4.01)	(2.29)	(6.51)
3	6 29**	9.33**	−3.67	−0.70	−0.16	4.48**	4.22*	8.73**
	(3.18)	(7.12)	(−0.94)	(−0.27)	(−0.06)	(2.71)	(2.07)	(6.29)
4	8.47**	12.20**	−1.00	2.35	0.82	5.79**	3.91	8.41**
	(3 96)	(8.89)	(−0.23)	(0.90)	(0.31)	(3 39)	(1.85)	(5.90)
5	11.04**	14.99**	3.30	7.22**	2.69	7.19**	4.39*	8.85**
	(4 99)	(10.36)	(0.72)	(2.64)	(0.99)	(4.00)	(2.10)	(6.31)
6	10.78**	15.02**	4.43	7.87**	3.17	8 36**	5.88**	10.32**
	(4 62)	(10.05)	(0.88)	(2.64)	(1.12)	(4 58)	(2.71)	(6.95)
7	10 67**	15.06**	9.72	12.95**	5.50	10 67**	6.15**	10.44**
	(4.42)	(9.48)	(1.78)	(4.02)	(1.85)	(5 50)	(2.75)	(6.87)
8	9.02**	13.60**	11.86*	14.96**	7.65*	13 53**	7.82**	11.77**
	(3.49)	(7.75)	(2.02)	(4.29)	(2.44)	(6 84)	(3.45)	(7.65)
9	8 21**	13.08**	14.94*	16.85**	9.12**	14 68**	8.18**	12.06**
	(3 30)	(7.48)	(2.42)	(4.25)	(2.72)	(6 56)	(3.36)	(7.21)
High	−2 93	1.76	24.05**	25.02**	15.13**	21.00**	12.52**	15.83**
	(−1.15)	(0.92)	(3.37)	(5.36)	(4.56)	(9.70)	(4.98)	(9.02)
High – Low	−8 53**	−6.83**	26.52**	24.59**	16.91**	19.16**	8.15**	7.99**
	(−4 69)	(−3.86)	(4.33)	(4.85)	(7.35)	(8.71)	(4.01)	(4 30)

not work well. However, the MA works well for the other 9 decile portfolios, with the alphas ranging from 8.58% to 15.06% per annum, and therefore the overall evidence is positive that the MA is profitable for all but 1 decile.

Interestingly, with the credit rating decile portfolios (Panel B of Table 3), the alphas increase monotonically from the lowest default risk decile (Low) to the highest default risk decile (High), and there is no sharp drop of performance at the highest default risk decile. This is due to the composition of different stocks in the extreme portfolios. However, it should be noted that the alphas are insignificant for the first 4 deciles. When the firms are of high credit, their fundamentals are likely very strong and informative. Consistent with Zhang (2006), there is likely much less trend and little profitability of the technical analysis. Overall, the MA works well for the credit rating portfolios: The alphas range from 7.22% to 25.02% per annum excluding the first 4 deciles. In fact, the credit rating decile portfolios generate the highest spread, or the difference in abnormal returns between the highest and the lowest default risk deciles, a striking 24.59% per annum, more than twice that generated by the volatility deciles.

Very similar results are obtained for decile portfolios sorted on analyst forecast dispersion (Panel C of Table 3). In general, the alphas increase monotonically from the lowest decile (Low) to the highest decile (High), and the spread between the two extreme deciles (High-Low) is the second highest, about 19.16% per annum, almost twice that generated by the volatility deciles. Finally, a similar monotonic relation between the abnormal returns and information uncertainty is observed for the income volatility decile portfolios (Panel D). The alphas increase monotonically from 7.83% per annum at the lowest income volatility decile (Low) to 15.83% per annum at the highest-volatility decile (High).

To summarize, while we acknowledge that we have examined only a few portfolio sortings, the results appear to show that the noise-to-signal ratio or information uncertainty is the key to superior performance of the MA timing strategy. When the noise-to-signal ratio is high, the fundamentals are less informative, and hence technical analysis becomes more profitable.

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 we consider the use of the value-weighted size decile portfolios. Finally, we analyze the trading behavior of the MA timing strategy and estimate the BETC.

A. Alternative Lag Lengths

Consider now the profitability of the MAPs by using 20-, 50-, 100-, and 200-day MAs. Table 4 reports both the average returns and Fama-French (1993) 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 MA 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 (1993) 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 2). 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 generates 5.76%, only about 29% of the risk-adjusted abnormal return of the 10-day MA.[8]

TABLE 4

Alternative Moving Averages Lag Lengths

Table 4 reports the average returns (Avg Ret) and the Fama-French (1993) 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 10,000 repeats. The results are annualized and in percentages. The Newey and West (1987) robust t-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively. The sample period is from July 1, 1963, to Dec. 31, 2009.

	MAP(20)		MAP(50)		MAP(100)		MAP(200)		Random Switching	
Rank	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α
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)

Second, similar to the 10-day MA timing strategy, all the other MA timing strategies generate monotonically increasing abnormal returns across the deciles,

[8]The reverse monotonic relation between the lag length and the profitability (not reported here) is no longer true for 3-day and 5-day lag lengths.

except for the highest decile case, where it has slightly lower values than those of the 9th 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 it is only 2.66% and insignificant when $L = 200$.

Finally, the last two columns in Table 4 provide the performance of a random switching strategy as a reference for the performance of the MA timing. The random switching strategy switches between the decile portfolios and the risk-free T-bills by random chance. In sharp contrast to the MA timing strategy, the random switching strategy yields significantly negative average returns and Fama-French (1993) alphas based on the average of 10,000 random switching portfolios. Furthermore, both returns decrease monotonically across the deciles, with the highest-volatility decile yielding an average return as low as −19.72% per annum.

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 compared to the value-weighted case. To mitigate this concern, we use the value-weighted CRSP size portfolios to further check the robustness of the results. The 10 value-weighted size decile portfolios are 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. This is important, since daily rebalancing is costly and impractical (see, e.g., Asparouhova, Bessembinder, and Kalcheva (2013)). The sample period for the size decile portfolios is from July 1, 1963, to Dec. 31, 2009, to coincide with the Fama-French (1993) factors. Since smaller size deciles have larger volatilities, the 10 size portfolios may be viewed approximately as another set of volatility decile portfolios.[9]

Table 5 reports the average returns and Fama-French (1993) alphas for the MAPs based on the size portfolios formed with value weighting based on stocks traded on NYSE/AMEX/NASDAQ. With the important exception of 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 only 3%–5% 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 13.27% to 22.06% per annum when $L = 10$. The last row provides the differences between the smallest and the largest deciles, which are both economically

[9]In unreported analysis, we form value-weighted volatility decile portfolios from stocks in the CRSP universe, and obtain similar results. For example, the average return (Fama-French (1993) alpha) of the MAP(10) ranges from 1.21% (3.22%) for the lowest decile to 20.99% (24.95%) for the 9th decile.

and statistically significant for all cases. Overall, it is clear that the profitability of the MA timing strategy remains strong with the use of the value-weighted size decile portfolios. Unlike the declining size effect, this is also true for recent periods, say from Jan. 2, 2004, to Dec. 31, 2004. The abnormal returns are as large as before in magnitude, and they are of great economic significance.

TABLE 5

Size Decile Portfolios

Table 5 reports the average returns (Avg Ret) and the Fama-French (1993) 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 percentages. The Newey and West (1987) robust *t*-statistics are in parentheses. ** and * indicate sign ficance at the 1% and 5% levels, respectively. The sample period is from July 1, 1963, to Dec. 31, 2009.

	MAP(10)		MAP(20)		MAP(50)		MAP(100)		MAP(200)	
Rank	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α
Large	0.18	3.18*	−0.01	2.88*	0.01	3.45*	−0.34	3.42*	0.80*	3.96**
	(0.09)	(2.45)	(−0.00)	(2.06)	(0.01)	(2.44)	(−0.17)	(2 38)	(0.01)	(0.40)
2	9.82**	13.27**	7.83**	11.68**	4 64*	8 85**	2.70	7.58**	0.89*	4.62*
	(4.44)	(9.53)	(3.41)	(7.60)	(1 98)	(5 57)	(1.15)	(4.74)	(0.00)	(0.39)
3	10.80**	14.36**	8.65**	13.00**	5 66*	10 54**	3 36	8.88**	1.27*	5.19*
	(4.76)	(9.97)	(3.68)	(8.27)	(2 35)	(6 53)	(1.42)	(5.55)	(0.00)	(0.55)
4	12.24**	15.73**	10.91**	15.39**	7 27**	12.08**	4.04	9.45**	1.80*	5.61**
	(5.37)	(10.88)	(4.70)	(10.10)	(3.02)	(7 58)	(1.70)	(5.85)	(0.00)	(0.78)
5	12.90**	16.26**	12.45**	16.86**	9.16**	14.06**	5.17*	10.70**	2.43*	6.17**
	(5.65)	(10.88)	(5.49)	(11.10)	(3 92)	(8 95)	(2 23)	(6.80)	(0.00)	(1.05)
6	14.88**	17.97**	14.05**	18.37**	10 36**	15.08**	6 58**	11.90**	3.64*	7.05**
	(6.78)	(12.28)	(6.42)	(12.59)	(4 55)	(9.70)	(2 89)	(7.52)	(0.00)	(1.63)
7	17.45**	19.99**	15.76**	18.98**	12.12**	15 62**	7 35**	11.11**	4.28*	6.89**
	(8.58)	(14.29)	(7.66)	(13.02)	(5.77)	(10.45)	(3.48)	(7.09)	(0.00)	(2.06)
8	19.37**	21.57**	17.73**	20.38**	13.45**	16.15**	8 31**	11.27**	4.67*	6.82**
	(9.94)	(15.40)	(8.93)	(14.23)	(6 56)	(10 64)	(3 98)	(7.01)	(0.00)	(2.26)
9	20.11**	22.06**	18.15**	20.44**	13.79**	16.08**	9.00**	11.52**	4.94*	6.71**
	(10.56)	(15.64)	(9.50)	(14.16)	(6 94)	(10 50)	(4.45)	(7.06)	(0.00)	(2.46)
Small	19.86**	21.66**	18.37**	20.39**	13 52**	15.42**	8 20**	10.34**	3.24*	4.76*
	(10.18)	(14.35)	(9.23)	(12.96)	(6 50)	(8 93)	(3 83)	(5.58)	(0.01)	(1.50)
Small – Large	19.68**	18.48**	18 38**	17.51**	13 51**	11.97**	8 54**	6.92**	2.44**	0.81
	(10.66)	(10.82)	(9.79)	(9.93)	(6 83)	(6.44)	(4.14)	(3.49)	(0.70)	(1.12)

C. Average Holding Days, Trading Frequency, and BETC

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, a real concern is whether the abnormal returns can survive transaction costs. We address this issue by analyzing the average consecutive holding days of the timing portfolios, their trading frequency, as well as the BETC, under which the average returns of the MAPs become 0.

The average consecutive holding days are reported in Table 6 for MA lag lengths from 10 days to 200 days. It is not surprising that longer lag lengths of MA signal 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 decile often has the longest holding days, whereas the highest-volatility decile often has the shortest holding days for the same MA lag length. 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" in Table 6. 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%, indicating very few trades for the 200-day MA strategy.

TABLE 6

Trading Frequency and BETC

Table 6 reports the average consecutive holding days (Holding), fraction of trading days (Trading), and break-even transaction costs (BETCs) in basis points 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 (MA) prices, respectively. The BETCs are calculated such that the average returns of the MAPs are 0. The sample period is from July 1, 1963, to Dec. 31, 2009.

	MA(10)			MA(20)			MA(50)			MA(100)			MA(200)		
Rank	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC
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

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 T-bill. Then, in the presence of transaction cost τ per trade, the returns on the MA timing strategy are

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

Determining the appropriate transaction cost level is always a difficult issue, and recent studies use a transaction cost level ranging from 1 basis point (bp) to 50 bp. For example, Balduzzi and Lynch (1999) use 1 bp and 50 bp as the lower and upper bounds for transaction costs, and Lynch and Balduzzi (2000) consider a transaction cost of 25 bp.[10] Without taking a stand on the level of the appropriate transaction costs, we consider the BETC that makes the average returns of the MAPs zero. Table 6 reports the BETC in basis points. Generally the BETC decreases across the volatility decile, with the lowest deciles having the highest BETC, which is consistent with the patterns of the average holding days and trading frequencies. Across different MA lag lengths, MA(50) has the highest BETC, as high as 111.52 bp, while MA(10) has the lowest BETC. The lowest BETC is with MA(10) decile 8, about 28.80 bp. Overall, the BETCs are reasonably high, which suggests that the MAPs should still earn economically highly significant abnormal returns after considering appropriate transaction costs.[11]

V. Comparison with Momentum

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

A. Momentum Betas

With returns on the UMD, which are readily available from Kenneth French's Web site (mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html), 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 correlations suggest that the MAPs may not be sensitive to the momentum factor in the following regression model:

$$\text{(7)} \qquad \begin{aligned} \text{MAP}_{jt,L} \quad = \quad & \alpha_j + \beta_{j,\text{MKT}} r_{\text{MKT},t} + \beta_{j,\text{SMB}} r_{\text{SMB},t} + \beta_{j,\text{HML}} r_{\text{HML},t} \\ & + \beta_{j,\text{UMD}} r_{\text{UMD},t} + \epsilon_{jt}, \qquad j = 1, \ldots, 10, \end{aligned}$$

where $r_{\text{MKT},t}$, $r_{\text{SMB},t}$, $r_{\text{HML},t}$, and $r_{\text{UMD},t}$ are the daily market excess return, the daily return on the SMB factor, the daily return on the HML factor, and the daily return on the UMD (momentum) factor, respectively.

Table 7 reports the regression results of the MAPs on the Fama-French (1993) 3 factors and the UMD. Clearly, momentum does not explain the abnormal returns of the MAPs. Similar to the CAPM model and Fama-French 3-factor model, the alphas are still significantly positive and monotonically increasing across the deciles except for the highest decile, for which the alpha is slightly reduced.

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

[11] The debate on the correct amount of transaction costs is unlikely to get resolved in our exploratory study here, but it is 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 the issue of transaction costs in their paper.

Moreover, the 4-factor alphas are even slightly larger than those of the CAPM and Fama-French models. This is due to the small negative exposure of the MAPs to the UMD.

TABLE 7

Alphas with the Momentum Factor

Table 7 reports the alphas, betas, and adjusted R^2s of the regressions of the MAPs, fo med from the 10-day MA timing strategy, on the Fama-French (1993) 3 factors and the momentum factor. The alphas are annualized and in percentages. The Newey and West (1987) robust *t*-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively. The sample period is from July 1, 1963, to Dec. 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)		

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 after controlling for the other factors, even though the magnitude is small. This is not surprising, since both are TFSes. However, the additional explanatory power of the UMD is quite small. The last column of Table 7 reports the differences of the adjusted R^2s between the 4-factor regressions and the Fama-French (1993) 3-factor regressions (Table 2). The incremental R^2s are all less than 1%. Therefore, we conclude that the MA timing strategy and the momentum strategy are substantially different TFSes. The question is whether there is any economic linkage between them, which we address later.

B. 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 gross domestic product (GDP) growth periods and explain that the earlier finding of Chordia and Shivakumar may be due to not skipping a month between ranking and investment periods and the National Bureau of Economic Research (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, Gutierrez, and Hameed (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 1, 2, or 3 years. Huang (2006) finds similar evidence in the international markets, and Chabot et al. 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 (1993) 3 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 8 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 may be smaller in recessions. In contrast, all the MAPs have significant coefficients for the *Recession* dummy variable. 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 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 2 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 8 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 following the down market, whereas the coefficient of the *Up Market* dummy variable is statistically significant and economically considerable, about 10.86% per annum, indicating significant momentum profits following the up market. In contrast, the coefficients

TABLE 8

Business Cycles and Up Markets

Panel A of Table 8 reports the regression results of the NYSE/AMEX volatility MAPs, fo med from the 10-day MA timing strategy, on the Fama-French (1993) 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 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 percentages. The Newey and West (1987) robust t-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively. The sample period is from July 1, 1963, to Dec. 31, 2009.

	Panel A. With Recession Dummy						*Panel B. With Up Market Dummy*					
Decile	α	β_{MKT}	β_{SMB}	β_{HML}	Recession	Adj. R^2 (%)	α	β_{MKT}	β_{SMB}	β_{HML}	Up Market	Adj. R^2 (%)
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)	

of the *Up Market* dummy variable 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 UMD, but similar to that of MAPs using the NBER recession dummy variable in Panel A.

VI. 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 examine whether the superior performance can be captured by a TFF constructed using lookback straddles. We finally examine whether exposures to other macroeconomic variables can explain the abnormal returns of the MAPs using conditional models.

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 (TM) (1966):

$$\text{(8)} \quad \text{MAP}_{jt,L} = \alpha_j + \beta_{j,\text{MKT}} r_{\text{MKT},t} + \beta_{j,\text{MKT}^2} r^2_{\text{MKT},t} + \epsilon_{jt}, \qquad j = 1, \ldots, 10,$$

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

$$\text{(9)} \quad \text{MAP}_{jt,L} = \alpha_j + \beta_{j,\text{MKT}} r_{\text{MKT},t} + \gamma_{j,\text{MKT}} r_{\text{MKT},t} I_{r_{\text{MKT}}>0} + \epsilon_{jt}, \qquad j = 1, \ldots, 10,$$

where $I_{r_{\text{MKT}}>0}$ is the indicator function taking the value of 1 when the market excess return is above 0, otherwise taking the value of 0. The significantly positive coefficient, γ_{MKT}, indicates successful market timing.

Table 9 provides evidence of successful market timing for the MA timing strategy. Panel A reports the coefficients of the quadratic regression (TM (1966)) of the MAPs, and Panel B reports the coefficients of the option-like regression

TABLE 9

Market Timing

Table 9 reports the alphas, betas, and adjusted R^2s of the market timing regressions of the volatility MAPs. Panel A is the Treynor and Mazuy (TM) (1966) quadratic regression with the squared market factor (β_{MKT^2}), and Panel B is the Henriksson and Merton (HM) (1981) regression with option-like returns on the market (γ_{MKT}), respectively. The alphas are annualized and in percentages. The Newey and West (1987) robust *t*-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively. The sample period is from July 1, 1963, to Dec. 31, 2009.

	Panel A. TM Regression				*Panel B. HM Regression*			
Rank	α	β_{MKT}	β_{MKT^2}	Adj. R^2 (%)	α	β_{MKT}	γ_{MKT}	Adj. R^2 (%)
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)	

(HM (1981)) of the MAPs. In Panel A, the market timing coefficients, β_{MKT^2}, are positive but mostly insignificant. On the other hand, the market timing coefficients in Panel B, γ_{MKT}, are significantly positive, indicating successful market timing by the MA timing strategy. As a result, the remaining abnormal returns are greatly reduced. However, market timing alone does not explain the abnormal returns of the MAPs, especially for the high-volatility deciles. For example, in Panel B, alphas of the higher-volatility deciles are still positive and significant, ranging from 5.50% to 9.06% per annum, even though alphas of the lower deciles become insignificant.

B. Benchmark against a Trend-Following Strategy

An interesting way to understand the MA strategy is from the perspective of options. Suppose the MA strategy is 100% successful; then its return would look like

$$\text{MAP}_j \quad = \quad \max(R_j, R_f) - R_j \quad = \quad \max(R_j - R_f, 0), \tag{10}$$

where R_j and R_f are the returns on the jth decile and risk-free asset, respectively.[12] That is, the payoff works like a put option written on the decile portfolio. To capture the option-like returns, following Fung and Hsieh (2001), we use lookback straddles to extract a risk factor of the TFS. A lookback straddle is a combination of a lookback call option, which gives the right to the buyer to buy the underlying asset at the lowest price over the life of the option, and a lookback put option, which gives the buyer the right to sell at the highest price. Thus, a lookback straddle delivers the ex post maximum payout of any TFS. Fung and Hsieh (2001) and Goldman, Sosin, and Gatto (1979) argue that TFSes should deliver returns resembling those of a portfolio of T-bills and lookback straddles.

Following Fung and Hsieh (2001), we form the lookback straddle on the Standard & Poor's (S&P) 500 index by dynamically rolling standard straddles over the life of the option. The rollover process is reminiscent of the buying breakout and selling breakdown characteristics of the TFSes. To extend the sample period, however, we use the daily level of the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) to back out both the call option and put option prices. We also use 1-month options instead of the 3-month options used in Fung and Hsieh. Our VIX daily series starts from Jan. 1990, so our sample period is from Feb. 1, 1990, to Dec. 31, 2009.

Table 10 reports the regression results of the MA(10) timing portfolios (Panel A) and MAPs (Panel B) on the Fama-French (1993) 3 factors plus the TFF. In Panel A, the loadings on the TFF, β_{TFF}, are all positive and significant. Furthermore, they increase across the volatility deciles from the lowest-volatility decile to the highest-volatility decile. However, the risk-adjusted abnormal returns (α) are, reduced only by a small amount, still positive and significant, and they monotonically increase across the volatility deciles. Panel B shows that the sensitivities of MAPs to the TFF are much weaker and sometimes insignificant.

[12]We are grateful to the referee for this intriguing interpretation and other insightful comments that helped to improve the paper substantially.

TABLE 10

Benchmark Against Trend-Following Strategy

Panel A of Table 10 reports the regression results of the timing portfolios, fo med from the 10-day MA timing strategy, on the Fama-French (1993) market portfolio, SMB and HML factors, and a trend-following factor (TFF) generated using lookback straddles on the S&P 500 index (Fung and Hsieh (2001)). Panel B reports similar regression results with the MAPs. The intercepts (αs) are annualized and in percentages. The Newey and West (1987) robust *t*-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively. The sample period is from Feb. 1, 1990, to Dec. 31, 2009.

	Panel A. MA(10) Timing Portfolios						*Panel B. MAP(10)*					
Rank	α	β_{MKT}	β_{SMB}	β_{HML}	$\beta_{\text{TFF}}(\times 100)$	Adj. R^2 (%)	α	β_{MKT}	β_{SMB}	β_{HML}	$\beta_{\text{TFF}}(\times 100)$	Adj. R^2 (%)
Low	10 89**	0.07**	–0.00	0.04**	0.02*	13 26	7.56**	–0.12**	0.02	–0.08**	0.01	16 96
	(10.70)	(10.81)	(–0.32)	(4.41)	(2.27)		(5.90)	(–4.49)	(0.61)	(–3.49)	(0 97)	
2	9.79**	0.18**	0.04**	0.08**	0.02*	33.71	7.05**	–0.27**	–0.01	–0.16**	0.03*	39 82
	(8 24)	(12.40)	(3.40)	(4.48)	(1.97)		(4.44)	(–8.12)	(–0.41)	(–4.79)	(2.19)	
3	9 89**	0.26**	0.05**	0.12**	0.04**	40.01	6.49**	–0.35**	–0.03	–0.16**	0.04**	46.07
	(6.76)	(12.33)	(3.19)	(4.62)	(2.53)		(3.79)	(–10.14)	(–1.08)	(–4 50)	(2 52)	
4	10 26**	0.33**	0.11**	0.19**	0.05**	41.01	7.65**	–0.43**	–0.06**	–0 20**	0.04*	49 29
	(5 94)	(11.61)	(5.04)	(5.40)	(2.77)		(4.07)	(–11.03)	(–2.60)	(–4.78)	(2 39)	
5	10 69**	0.37**	0.19**	0.22**	0.05**	40.10	9.37**	–0.51**	–0.12**	–0 26**	0.04	52.48
	(5 64)	(10.39)	(6.60)	(4.93)	(2.54)		(4.54)	(–11.60)	(–4.44)	(–5.07)	(1.77)	
6	12 51**	0.39**	0.24**	0.26**	0.06**	39 67	10.47**	–0.55**	–0.16**	–0 27**	0.04	53 35
	(5 95)	(10.59)	(7.95)	(5.32)	(2.55)		(4.89)	(–12.88)	(–6.06)	(–5.42)	(1 86)	
7	13 21**	0.42**	0.31**	0.27**	0.06*	39.48	11.41**	–0.59**	–0.21**	–0 26**	0.04*	53 84
	(5.78)	(10.61)	(9.63)	(5.08)	(2.39)		(4.86)	(–13.24)	(–6.98)	(–4 98)	(1 92)	
8	17 99**	0.44**	0.37**	0.29**	0.08**	39 31	16.35**	–0.61**	–0.25**	–0 22**	0.05*	53.14
	(7.09)	(10.61)	(11.33)	(4.85)	(3.19)		(6.72)	(–14.56)	(–8.08)	(–4.15)	(2.18)	
9	27.15**	0.47**	0.40**	0.30**	0.12**	37.75	19.85**	–0.61**	–0.32**	–0.17**	0.05	49.40
	(8 93)	(11.04)	(12.49)	(4.76)	(4.25)		(7.15)	(–14.38)	(–9.48)	(–3.13)	(1 64)	
High	64.76**	0.40**	0.46**	0.31**	0.22**	23 54	17.72**	–0.49**	–0.32**	–0 20**	0.05	37.77
	(12 83)	(10.65)	(12.31)	(5.02)	(4.24)		(6.18)	(–12.17)	(–7.31)	(–3.44)	(1 55)	
High –	53 87**	0.33**	0.47**	0.27**	0.20**		10.16**	–0.37**	–0.34**	–0.12**	0.04	
Low	(10 96)	(9.64)	(12.71)	(4.72)	(4.02)		(3.67)	(–11.71)	(–8.87)	(–2.45)	(1.39)	

The risk-adjusted abnormal returns are still positive and significant. In short, like the CAPM and Fama-French models, the TFF cannot explain the superior performance of the MA timing strategy. A likely reason is that the cross-sectional trends are unlikely to coincide with the aggregate market. Theoretically, Merton (1981) shows that, in the absence of no short-sale constraints, the market timing strategy generates returns similar to a portfolio of T-bills and a straddle. In this sense, the result of this section is consistent with the previous one.

C. Conditional Models with Macroeconomic Variables

Ferson and Schadt (1996) advocate using 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 (1993) 3-factor model to measure the abnormal returns of the MAPs.

The conditional model is specified as

$$
\text{(11)} \qquad \begin{aligned} \text{MAP}_{jt,L} \;=\;& \alpha_j + \beta_{j,\text{MKT}} r_{\text{MKT},t} + \beta_{j,\text{SMB}} r_{\text{SMB},t} + \beta_{j,\text{HML}} r_{\text{HML},t} \\ & + \beta_{j,Z} Z_{t-1} + \gamma_{j,S} Z_{t-1} r_{\text{MKT},t} + \epsilon_{jt}, \qquad j = 1, \ldots, 10, \end{aligned}
$$

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. Stambaugh et al. (2012) find that many anomalies are sensitive to investor sentiment.

Panel A in Table 11 reports the results of the conditional Fama-French (1993) model with monthly changes in investor sentiment (ΔSent). Both coefficients of

TABLE 11

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

Table 11 reports the regression results of the NYSE/AMEX volatility MAPs, fo med from the 10-day MA timing strategy, using the conditional Fama-French (1993) 3-factor models:

$$\text{MAP}_{jt,L} = \alpha_j + \beta_{j,\text{MKT}} r_{\text{MKT},t} + \beta_{j,\text{SMB}} r_{\text{SMB},t} + \beta_{j,\text{HML}} r_{\text{HML},t} + \beta_{j,Z} Z_{t-1} + \gamma_{j,S} Z_{t-1} r_{\text{MKT},t} + \epsilon_{jt}.$$

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 (Pastor and Stambaugh (2003)), and Panel D reports the results with all three variables above plus a recession dummy variable. The Fama-French alphas are annualized and in percentages, and the other coefficients are also scaled for ease of presentation. The Newey and West (1987) robust t-statistics are in parentheses. ** and * indicate significance at the 1% and 5% levels, respectively. The sample period in Panel A is from July 1, 1965, to Dec. 31, 2007; in Panel C it is from July 1, 1968, to Dec. 31, 2009; and in Panel D it is from July 1, 1968, to Dec. 31, 2007, due to data availability.

	Panel A. Sentiment				*Panel B. Default Spread*				*Panel C. Liquidity*			
Decile	FF α	ΔSent	ΔSent × r_{MKT}	Adj. R^2 (%)	FF α	Default	Default × r_{MKT}	Adj. R^2 (%)	FF α	Liquid	Liquid × r_{MKT}	Adj. R^2 (%)
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)	

(continued on next page)

TABLE 11 (continued)

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

	Panel D. Sentiment, Default Spread, Liquidity, and Recession Dummy									
Decile	FF α	ΔSent	Default	Liquid	Recession	ΔSent $\times$ r_{MKT}	Default $\times$ r_{MKT}	Liquid $\times$ r_{MKT}	Recession $\times$ 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)	

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 3-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), and Collin-Dufresne, Goldstein, and Martin (2001) use stock volatility as the most important factor driving the credit risk. Many empirical studies, such as Ericsson, Jacobs, and Oviedo (2009), also link stock volatility to default spread. Panel B of Table 11 reports the results of regressing the MAPs on the Fama-French (1993) 3 factors and the default spread. Similar to the case of investor sentiment, the MAPs are insensitive to the default spread: Both of the coefficients are positive but insignificant for all deciles but the lowest one, which has a significant coefficient for the interaction term.

Stock volatility is closely related to liquidity. Stoll (1978) and 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. Therefore, exposure to liquidity may explain the abnormal returns of the MAPs. Panel C of Table 11 reports the results of regressing the MAP portfolios on the Fama-French (1993) 3 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 (1993) conditional model and also add the recession dummy variable. The results are reported in Panel D of Table 11. Similar to Table 8, the recession dummy variable is still significantly positive; however, the coefficient of the product of the recession dummy variable 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.

VII. Concluding Remarks

In this paper, we document that a standard moving average (MA) of technical analysis, when applied to portfolios sorted by volatility, can generate investment timing portfolios that greatly outperform the buy-and-hold strategy. In addition, the differences in the two returns have negative or little risk exposures to the market factor and the Fama-French (1993) SMB and HML factors. Especially for the high-volatility portfolios, the abnormal returns, relative to the CAPM and the Fama and French 3-factor models, are extremely high, and much higher than those from the momentum strategy. Moreover, the MA strategy obtains similar abnormal returns for decile portfolios sorted on size, distance to default measure, credit rating, analyst forecast dispersion, and income volatility, which are proxies for information uncertainty. While the MA strategy is a trend-following one similar to the momentum strategy, its performance has little correlation with the momentum strategy, and it behaves differently over business cycles. The abnormal returns cannot be explained by market timing or by the trend-following factor of Fung and Hsieh (2001), nor are they sensitive to changes in investor sentiment, default, and liquidity risks.

Our study provides a new research avenue in several directions. First, our study suggests that it likely will be 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 and other information uncertainty proxies. 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 MA anomaly with new asset pricing models will be important and desirable. Third, because of its trend-following nature, various investment issues that have been investigated around the momentum strategy can also be investigated with the MA strategy. All of these are interesting topics for future research.[13]

[13]Han, Wang, Zhou, and Zou (2013) find robustness of the results in China, while Han and Zhou (2013a), (2013b) extend the MA strategy to yield a trend factor and a twin momentum anomaly.

References

Ang, A., and G. Bekaert. "Stock Return Predictability: Is It There?" *Review of Financial Studies*, 20 (2007), 651–707.

Ang, A.; R. J. Hodrick; Y. Xing; and X. Zhang. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance*, 61 (2006), 259–299.

Asparouhova, E.; H. Bessembinder; and I. Kalcheva. "Noisy Prices and Inference Regarding Returns." *Journal of Finance*, 68 (2013), 665–714.

Avramov, D.; T. Chordia; G. Jostova; and A. Philipov. "Dispersion in Analysts' Earnings Forecasts and Credit Rating." *Journal of Financial Economics*, 91 (2009), 83–101.

Baker, M. P., and J. Wurgler. "Investor Sentiment and the Cross-Section of Stock Returns." *Journal of Finance*, 61 (2006), 1645–1680.

Baker, M. P., and J. Wurgler. "Investor Sentiment in the Stock Market." *Journal of Economic Perspectives*, 21 (2007), 129–151.

Balduzzi, P., and A. W. Lynch. "Transaction Costs and Predictability: Some Utility Cost Calculations." *Journal of Financial Economics*, 52 (1999), 47–78.

Barberis, N.; A. Shleifer; and R. Vishny. "A Model of Investor Sentiment." *Journal of Financial Economics*, 49 (1998), 307–343.

Berkman, H.; V. Dimitrov; P. C. Jain; P. D. Koch; and S. Tice. "Sell on the News: Differences of Opinion, Short-Sales Constraints, and Returns around Earnings Announcements." *Journal of Financial Economics*, 92 (2009), 376–399.

Bharath, S. T., and T. Shumway. "Forecasting Default with the Merton Distance to Default Model." *Review of Financial Studies*, 21 (2008), 1339–1369.

Blume, L.; D. Easley; and M. O'Hara. "Market Statistics and Technical Analysis: The Role of Volume." *Journal of Finance*, 49 (1994), 153–181.

Brock, W.; J. Lakonishok; and B. LeBaron. "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns." *Journal of Finance*, 47 (1992), 1731–1764.

Brown, D. P., and R. H. Jennings. "On Technical Analysis." *Review of Financial Studies*, 2 (1989), 527–551.

Campbell, J. Y., and S. B. Thompson. "Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average?" *Review of Financial Studies*, 21 (2008), 1509–1531.

Cespa, G., and X. Vives. "Dynamic Trading and Asset Prices: Keynes vs. Hayek." *Review of Economic Studies*, 79 (2012), 539–580.

Chabot, B. R.; E. Ghysels; and R. Jagannathan. "Momentum Cycles and Limits to Arbitrage: Evidence from Victorian England and Post-Depression U.S. Stock Markets." Working Paper, University of North Carolina-Chapel Hill and Northwestern University (2010).

Chincarini, L. B., and D. Kim. *Quantitative Equity Portfolio Management: An Active Approach to Portfolio Construction and Management*. New York, NY: McGraw-Hill (2006).

Chordia, T., and L. Shivakumar. "Momentum, Business Cycle, and Time-Varying Expected Returns." *Journal of Finance*, 57 (2002), 985–1019.

Cochrane, J. H. "The Dog That Did Not Bark: A Defense of Return Predictability." *Review of Financial Studies*, 21 (2008), 1533–1575.

Collin-Dufresne, P.; R. S. Goldstein; and J. S. Martin. "The Determinants of Credit Spread Changes." *Journal of Finance*, 56 (2001), 2177–2207.

Cooper, M. J.; R. C. Gutierrez, Jr.; and A. S. Hameed. "Market States and Momentum." *Journal of Finance*, 59 (2004), 1345–1365.

Covel, M. W. *Trend Following: How Great Traders Make Millions in Up or Down Markets*. New York, NY: Prentice-Hall (2005).

Cowles, A. "Can Stock Market Forecasters Forecast?" *Econometrica*, 1 (1933), 309–324.

Daniel, K.; D. Hirshleifer; and A. Subrahmanyam. "Investor Psychology and Security Market Under- and Overreactions." *Journal of Finance*, 53 (1998), 1839–1885.

Diether, K. B.; C. J. Malloy; and A. Scherbina. "Differences of Opinion and the Cross Section of Stock Returns." *Journal of Finance*, 57 (2002), 2113–2141.

Ericsson, J.; K. Jacobs; and R. Oviedo. "The Determinants of Credit Default Swap Premia." *Journal of Financial and Quantitative Analysis*, 44 (2009), 109–132.

Faber, M. T. "A Quantitative Approach to Tactical Asset Allocation." *Journal of Wealth Management*, 9 (2007), 69–79.

Fama, E. F., and K. R. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3–56.

Fama, E. F., and W. Schwert. "Asset Returns and Inflation." *Journal of Financial Economics*, 5 (1977), 115–146.

Ferson, W. E., and C. R. Harvey. "The Variation of Economic Risk Premiums." *Journal of Political Economy*, 99 (1991), 385–415.

Ferson, W. E., and R. W. Schadt. "Measuring Fund Strategy and Performance in Changing Economic Conditions." *Journal of Finance*, 51 (1996), 425–461.

Fung, W., and D. A. Hsieh. "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers." *Review of Financial Studies*, 14 (2001), 313–341.

Gehrig, T., and L. Menkhoff. "Extended Evidence on the Use of Technical Analysis in Foreign Exchange." *International Journal of Finance and Economics*, 11 (2006), 327–338.

Goh, J.; F. Jiang; J. Tu; and G. Zhou. "Forecasting Government Bond Risk Premia Using Technical Indicators." Working Paper, Singapore Management University and Washington University in St. Louis (2013).

Goldman, M. B.; H. B. Sosin, and M. A. Gatto. "Path Dependent Options: 'Buy at the Low, Sell at the High.' " *Journal of Finance*, 34 (1979), 1111–1127.

Griffin, J. M.; X. Ji; and J. Martin. "Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole." *Journal of Finance*, 58 (2003), 2515–2547.

Han, Y. "Asset Allocation with a High Dimensional Latent Factor Stochastic Volatility Model." *Review of Financial Studies*, 19 (2006), 237–271.

Han, Y., and D. A. Lesmond. "Liquidity Biases and the Pricing of Cross-Sectional Idiosyncratic Volatility." *Review of Financial Studies*, 24 (2011), 1590–1629.

Han, Y.; X. Wang; G. Zhou; and H. Zou. "Are There Trends in Chinese Stock Market?" Working Paper, University of Colorado Denver and Washington University in St. Louis (2013).

Han, Y., and G. Zhou. "Trend Factor: A New Determinant of Cross-Section Stock Returns." Working Paper, University of Colorado Denver and Washington University in St. Louis (2013a).

Han, Y., and G. Zhou. "Twin Momentums in the Stock Market." Working Paper, University of Colorado Denver and Washington University in St. Louis (2013b).

Henriksson, R. D., and R. C. Merton. "On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills." *Journal of Business*, 54 (1981), 513–533.

Hjalmarsson, E. "Predicting Global Stock Returns." *Journal of Financial and Quantitative Analysis*, 45 (2010), 49–80.

Hong, H., and J. C. Stein. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *Journal of Finance*, 54 (1999), 2143–2184.

Huang, D. "Market States and International Momentum Strategies." *Quarterly Review of Economics and Finance*, 46 (2006), 437–446.

Jegadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, 48 (1993), 65–91.

LeBaron, B. "Technical Trading Rule Profitability and Foreign Exchange Intervention." *Journal of International Economics*, 49 (1999), 125–143.

Leland, H. E., and K. B. Toft. "Optimal Capital Structure, Endogenous Bankruptcy, and the Term Structure of Credit Spreads." *Journal of Finance*, 51 (1996), 987–1019.

Lo, A. W., and J. Hasanhodzic. *The Heretics of Finance: Conversations with Leading Practitioners of Technical Analysis*. New York, NY: Bloomberg Press (2009).

Lo, A. W.; H. Mamaysky; and J. Wang. "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation." *Journal of Finance*, 55 (2000), 1705–1770.

Longstaff, F. A., and E. S. Schwartz. "A Simple Approach to Valuing Risky Fixed and Floating Rate Debt." *Journal of Finance*, 50 (1995), 789–819.

Lynch, A. W., and P. Balduzzi. "Predictability and Transaction Costs: The Impact on Rebalancing Rules and Behavior." *Journal of Finance*, 66 (2000), 2285–2309.

Merton, R. C. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance*, 29 (1974), 449–470.

Merton, R. C. "On Market Timing and Investment Performance. I. An Equilibrium Theory of Value for Market Forecasts." *Journal of Business*, 54 (1981), 363–406.

Neely, C. J. "The Temporal Pattern of Trading Rule Returns and Central Bank Intervention: Intervention Does Not Generate Technical Trading Rule Profits." Working Paper, Federal Reserve Bank of St. Louis (2002).

Neely, C. J.; D. E. Rapach; J. Tu; and G. Zhou. "Forecasting the Equity Risk Premium: The Role of Technical Indicators." *Management Science*, forthcoming (2013).

Newey, W. K., and K. D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), 703–708.

Pástor, L., and R. F. Stambaugh. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy*, 111 (2003), 642–685.

Rapach, D. E.; J. K. Strauss; and G. Zhou. "Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy." *Review of Financial Studies*, 23 (2010), 821–862.

Rapach, D. E.; J. K. Strauss; and G. Zhou. "International Stock Return Predictability: What Is the Role of the United States?" *Journal of Finance*, 68 (2013), 1633–1662.

Schwager, J. D. *Market Wizards: Interviews with Top Traders*. New York, NY: Collins (1993).
Schwert, G. W. "Anomalies and Market Efficiency." In *Handbook of the Economics of Finance*, Vol. 1, G. M. Constantinides, M. Harris, and R. M. Stulz, eds. Amsterdam, Netherlands: Elsevier (2003), 939–974.
Spiegel, M., and X. Wang. "Cross-Sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk." Working Paper, Yale University (2005).
Stambaugh, R. F.; J. Yu; and Y. Yuan. "The Short of It: Investor Sentiment and Anomalies." *Journal of Financial Economics*, 104 (2012), 288–302.
Stoll, H. R. "The Pricing of Security Dealer Services: An Empirical Study of Nasdaq Stocks." *Journal of Finance*, 33 (1978), 1153–1172.
Treynor, J. L., and K. Mazuy. "Can Mutual Funds Outguess the Market?" *Harvard Business Review*, 44 (1966), 131–136.
Wilcox, C., and E. Crittenden. "Does Trend Following Work on Stocks?" Working Paper, Blackstar Funds, LLC (2009).
Zhang, X. F. "Information Uncertainty and Stock Returns." *Journal of Finance*, 61 (2006), 105–137.
Zhou, G., and Y. Zhu. "An Equilibrium Model of Moving-Average Predictability and Time-Series Momentum." Working Paper, Tsinghua University and Washington University in St. Louis (2013).
Zhu, Y., and G. Zhou. "Technical Analysis: An Asset Allocation Perspective on the Use of Moving Averages." *Journal of Financial Economics*, 92 (2009), 519–544.