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Value investing and technical analysis in Taiwan stock market[☆]

Kuan-Cheng Ko[a,*], Shinn-Juh Lin[b], Hsiang-Ju Su[a], Hsing-Hua Chang[c]

[a] Department of Banking and Finance, National Chi Nan University, Puli 54561, Taiwan
[b] Department of International Business, National Chengchi University, Taipei 11605, Taiwan
[c] Department of Money and Banking, National Chengchi University, Taipei 11605, Taiwan

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ABSTRACT

Unlike the U.S. and most developed countries, Taiwan stock market has been widely documented to have no value premium. Prior studies on the value premium typically adopt a conventional approach proposed by Fama and French (1992), which suggests a buy-and-hold strategy with annual rebalancing. We argue that a sophisticated investor can do better (obtain higher returns) than a simple buy-and-hold strategy by timing the market with the help of some technical analysis. Specifically, we show that an application of a moving average timing strategy to portfolios sorted by book-to-market (BM) ratios could generate higher returns than the buy-and-hold strategy. Using common stocks listed on the Taiwan Stock Exchange (TWSE), we confirm that the moving average timing strategy does substantially outperform the buy-and-hold strategy. Taking advantage of this observation, we propose a zero-cost portfolio constructed by buying the highest BM portfolio, and short-selling the lowest BM portfolio based on trading signals issued by the moving average rule, and demonstrate that such a new investment strategy can produce significantly positive returns. Robustness of results obtained in this paper is further verified and consolidated by extending the empirical study with a different currency, alternative lag lengths, transaction cost, subperiod analysis, business cycles and market timing.

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* Corresponding author at: No. 1, University Rd., Puli 54561, Taiwan. Tel.: +886 49 6003100x4695; fax: +886 49 2914511.
E-mail address: kcko@ncnu.edu.tw (K.-C. Ko).

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1. Introduction

The value premium, which states that stocks with high book-to-market (BM) ratios yield higher returns than those with low BM ratios, has been extensively documented in both the U.S. and international stock markets over the past two decades. Fama and French (1992, 1996), Lakonishok, Shleifer, and Vishny (1994) and Loughran (1997) all show that the value premium is a prevalent phenomenon in the U.S. market. As for the international evidence, Chan, Hamao, and Lakonishok (1991), Roll (1995), Mukherji, Dhatt, and Kim (1997), Bauman, Conover, and Miller (1998), Fama and French (1998), and Daniel, Titman, and Wei (2001) all demonstrate the existence of the value premium, either in a specific country outside the U.S. or on an aggregate basis across countries.

The evidence of the value premium in emerging markets or Asian markets, however, is somehow mixed and less pronounced. For example, out of the 20 emerging countries being examined, Rouwenhorst (1999) finds that high BM stocks have higher returns than low BM stocks in 16 of them, but significantly positive premiums only exist in Brazil, Korea, Malaysia and Zimbabwe. Furthermore, some countries such as Colombia, Pakistan, Portugal and Thailand even carry negative premium. For Asian markets, Mukherji et al. (1997), Chen and Zhang (1998), Chui and Wei (1998) and Ding, Chua, and Fetherston (2005) show that high BM stocks outperform growth stocks in Japan, Hong Kong, Korea, Malaysia and Singapore, but not in Indonesia, Taiwan and Thailand.

Brown, Rhee, and Zhang (2008) show that, after controlling for size and liquidity effects, there exist significant value premiums in Hong Kong, Korea and Singapore, but value discounts in Taiwan.

One thing in common among the aforementioned studies is the adoption of a conventional approach proposed by Fama and French (1992), which suggests a buy-and-hold strategy with annual rebalancing. Specifically, at the beginning of July in a given year, an individual firm's BM ratio is evaluated as its book value of equity divided by its market value of equity at the end of December in previous fiscal year. After assigning individual stocks into a particular portfolio according to their BM ratios, investors are assumed to sell short the low BM portfolio, and to use the proceeds to invest in the high BM portfolio simultaneously from July of year t to June of year $t + 1$ The value premium is then defined as the return of such a zero-cost value-minus-growth portfolio, which is assumed to be held for one year with annual rebalancing.

But, is the buy-and-hold strategy necessarily good for investors? What if the value premium exhibits some predictable patterns? Indeed, Cohen, Polk, and Vuolteenaho (2003) document statistically strong results concerning the predictability of returns on the value-minus-growth strategy. They show that the expected return on the value-minus-growth strategy is high when the spread in BM ratios is wide. In addition, if some sophisticated investors are able to "time the market", a better trading strategy for investors might be to invest in the value-minus-growth strategy only when the value premium is positive and significant.

Therefore, the main question we address in this paper is whether trading signals generated by some technical analyses can contribute incremental value to the value-investing strategy, even in a market absent of the BM effect.

Prior studies have already demonstrated the usefulness of technical analysis on some investment strategies. For example, Brock, Lakonishok, and LeBaron (1992), Brown and Jennings (1989), Lo, Mamaysky, and Wang (2000) and Neely, Rapach, Tu, and Zhou (2011) all find that technical analysis adds value in investing stock or market returns. Zhu and Zhou (2009) find that a trading rule based on the moving average (MA) provides additional information for the fixed-proportion strategy that follows Markowitz's (1952) modern portfolio theory and Tobin's (1958) two-fund separation theorem. Han, Yang, and Zhou (forthcoming) show that an application of the MA rule to portfolios sorted by volatility can generate reliably higher returns than the traditional buy-and-hold strategy. However, the usefulness of technical analysis documented in these studies is theoretically or empirically conducted based on particular strategies that have been documented to be profitable with prior data. But, if a given style investing strategy has been verified to produce no premium in one country, does such investment strategy combined with technical analysis become profitable?

We answer this question by linking value strategies based on BM portfolios and MA signals in Taiwan stock market, which is chosen for two main reasons.

First, Taiwan has been widely documented to have no value premium (Brown et al., 2008; Chen & Zhang, 1998; Chui & Wei, 1998; Ding et al., 2005; Hung, Chiao, Liao, & Huang, 2012), hence it serves as a natural experimental environment to examine the pure effect of technical analysis on value investing. Second, as argued by Zhu and Zhou (2009) and Han et al. (forthcoming), incomplete information on the fundamentals is a key for investors to use technical analysis. Since the degree of information incompleteness in an emerging market like Taiwan would be more severe than those in developed markets, technical analysis is more important for investors in Taiwan.

With a sample containing all common stocks listed on the TWSE from January 1980 to December 2010, we first confirm that the standard long-short BM portfolio based on buy-and-hold strategy does not produce significantly positive premium. After considering the buy or sell signals implied by the MA rule as suggested by Han et al. (forthcoming), we show that the 10-day MA timing strategies outperform the buy-and-hold strategies for all of the ten BM decile portfolios. Abnormal returns between the MA timing strategies and the buy-and-hold strategies cannot be explained by either the capital asset pricing model (CAPM) or Fama and French's (1993) three-factor model. Given the fact that MA signals are able to enhance the profitability of all BM portfolios, a simple difference between the highest and lowest BM portfolios under MA timing strategies still fails to produce significant premium.

We argue that the simple difference between the highest and lowest BM timing portfolios implies that investors sell short the lowest BM portfolio when the index price is higher than its MA indicator, which is in contradiction to the spirit of the MA rule. Hence, we propose a new strategy (TLS) to construct the zero-cost long-short portfolio by buying the highest BM portfolio when its index price is higher than its MA indicator, and by short-selling the lowest BM portfolio when its index price is lower than its MA indicator. We document a significantly positive premium of 21.953 (16.277) basis points per day for the equally-weighted (value-weighted) TLS strategy, which amounts to an annual return of 54% (40%) per annum. High premiums are not explained by the CAPM or Fama and French's (1993) three-factor model. For example, the TLS strategy with equal weights has a CAPM-adjusted return of 22.500 basis points per day, and a Fama–French risk-adjusted return of 22.864 basis points per day.

We test the robustness of our results in several ways. First, the main context of this paper is performed based on prices and returns in the local currency. We examine whether our results are affected by exchange rates by converting them into U.S. dollars, and show that our results remain unchanged. Second, we consider alternative lag lengths, including 5, 20, 50, 100, and 200 days, for the moving averages. We find that the abnormal BM premiums under MA timing strategies tend to be higher in short-horizon, with decreasing magnitude over the lag lengths. Nevertheless, the BM premiums are still significantly positive with the long lag lengths. Third, we examine the trading behavior, trading frequencies and break-even transaction costs of these MA timing portfolios. We show that investors do not have to trade these portfolios very often implied by MA signals and that the break-even transaction costs are reasonably large. Fourth, we show that our results sustain in subperiods, and are thus free from the data mining problem. We further show that our results are not driven by business cycles.

Finally, we analyze the source of the superior performance of the TLS strategy by examining whether the TLS strategy reveals any market timing ability. By applying two approaches proposed by Treynor and Mazuy (1966) and Henriksson and Merton (1981), we show supporting evidence for the market timing ability of the TLS strategy. However, market timing alone does not explain abnormal returns of the TLS strategy.

The rest of the paper is organized as follows. Section 2 describes the investment timing strategy using the MA as the timing signal, and the data used in this paper. In Section 3, we document the evidence for the profitability of the MA timing strategy, as well as the significance of the BM premium conditioning on the MA timing strategy. The robustness of profitability in a number of dimensions is examined with results presented in Section 4. The last section gives concluding remarks.

2. Methodology and data

We first discuss the construction of the test portfolios formed on BM, as well as the investment timing strategy based on the MA in Section 2.1. To examine whether the BM effect is strengthened when the MA

Table 1
Returns of BM decile portfolios, MA(10) timing portfolios, and MAPs. We follow Fama and French (1992) in constructing 10 equally- and value-weighted portfolios based on individual stocks' BM ratios. We calculate the 10-day moving average prices for each of the 10 BM portfolios each day using the last 10 days' closing prices, and compare the moving average price with the current price as the timing signal. If the current price is above the moving average price, we will invest in the decile portfolios for the next trading day; otherwise we will invest in the Central Bank discount rate for the next trading day. We report the average return (Avg Ret), the standard deviation (Std Dev), and the skewness (Skew) for the buy-and-hold benchmark decile portfolios, the moving average timing decile portfolios, and the moving average portfolios that are the differences between the MA timing portfolios and the buy-and-hold portfolios. The numbers are in basis points; in parentheses are Newey and West's (1987) t-statistics. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Rank	BM decile portfolios			MA(10) timing portfolios			MAPs		
	Ave Ret	Std Dev	Skew	Ave Ret	Std Dev	Skew	Ave Ret	Std Dev	Skew
Panel A: Equally-weighted portfolios									
Low	6.144	1.802	−0.119	13.805	1.177	0.248	7.661	1.358	0.290
2	5.008	1.740	−0.160	12.290	1.144	0.131	7.281	1.306	0.345
3	6.135	1.703	−0.212	13.447	1.130	0.033	7.312	1.267	0.390
4	4.500	1.729	−0.214	12.509	1.133	0.059	8.009	1.299	0.426
5	5.891	1.707	−0.237	12.711	1.134	0.043	6.819	1.269	0.468
6	5.902	1.701	−0.202	12.505	1.123	0.038	6.603	1.272	0.368
7	5.323	1.727	−0.208	13.451	1.149	0.044	8.128	1.282	0.410
8	6.033	1.763	−0.192	14.074	1.168	0.137	8.041	1.313	0.416
9	5.743	1.806	−0.163	15.062	1.217	0.191	9.319	1.325	0.429
High	5.648	1.695	0.843	15.430	1.131	0.372	9.782	1.251	−1.969
High–Low	−0.478	1.514	1.158	1.644	1.279	0.183	2.122	1.237	−1.946
	(−0.21)			(0.91)			(1.33)		
TLS	–			21.953***	1.616	0.135	22.431***	1.594	−1.002
				(10.22)			(11.16)		
Panel B: Value-weighted portfolios									
Low	7.096	1.866	0.022	11.068	1.284	0.373	3.972	1.351	0.126
2	5.019	1.770	−0.091	8.478	1.179	0.128	3.459	1.318	0.211
3	6.414	1.745	−0.121	9.964	1.186	0.035	3.550	1.277	0.206
4	4.171	1.789	−0.156	7.317	1.176	−0.049	3.146	1.346	0.252
5	6.532	1.856	−0.154	10.325	1.251	0.035	3.793	1.367	0.285
6	5.233	1.834	−0.121	9.053	1.238	−0.007	3.819	1.352	0.196
7	5.312	1.877	−0.136	11.483	1.274	0.079	6.172	1.373	0.303
8	7.044	1.890	−0.100	12.222	1.272	0.134	5.178	1.393	0.211
9	5.331	1.927	−0.161	13.266	1.297	0.126	7.935	1.419	0.387
High	6.188	1.970	−0.096	13.442	1.357	0.198	7.253	1.422	0.309
High–Low	−0.888	1.740	−0.019	2.395	1.505	0.039	3.283*	1.361	0.186
	(−0.36)			(1.18)			(1.94)		
TLS	–			16.277***	1.746	0.089	17.165***	1.781	0.188
				(7.26)			(7.54)		

signals are used to time the investment, we propose a zero-cost strategy based on the MA in Section 2.2. Section 2.3 describes the data used in this paper.

2.1. The moving average timing strategies

We construct 10 BM test portfolios in a similar way to that of Fama and French (1992). At the beginning of July in year t, we allocate individual stocks into ten deciles according to theirBM ratios at the end of December in year $t - 1$. Once stocks are assigned to portfolios, we calculate equally- and value-weighted daily index prices and returns of these portfolios from the beginning of July in year t to the end of June in year $t + 1$. That is, the portfolios are rebalanced annually.

Table 2
CAPM and Fama–French alphas of MAPs. We perform the time-series regressions of the MAPs formed from the 10-day MA timing strategy on CAPM and on Fama and French's (1993) three-factor model. The alphas, betas and the adjusted R^2 are reported; in parentheses are Newey and West's (1987) t-statistics. The alphas are in basis points. Panel A reports the results of equally-weighted portfolios, while Panel B reports the results of value-weighted portfolios. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Rank	CAPM			Fama–French model				
	α	β_{MKT}	Adj. R^2	α	β_{MKT}	β_{SMB}	β_{HML}	Adj. R^2
Panel A: Equally-weighted portfolios								
Low	9.955***	−0.561***	49.11	8.534***	−0.582***	−0.227***	0.122***	51.57
	(9.04)	(−86.46)		(7.92)	(−89.57)	(−15.84)	(11.55)	
2	9.466***	−0.535***	48.33	8.169***	−0.565***	−0.299***	0.011	51.39
	(8.87)	(−85.13)		(7.87)	(−90.25)	(−21.67)	(1.11)	
3	9.421***	−0.516***	47.85	8.310***	−0.548***	−0.309***	−0.039***	51.44
	(9.06)	(−84.31)		(8.25)	(−90.32)	(−23.08)	(−3.98)	
4	10.150***	−0.524***	46.86	8.937***	−0.563***	−0.378***	−0.091***	52.32
	(9.43)	(−82.66)		(8.73)	(−91.34)	(−27.74)	(−9.08)	
5	8.915***	−0.513***	47.06	8.172***	−0.547***	−0.313***	−0.124***	51.66
	(8.49)	(−82.99)		(8.12)	(−90.09)	(−23.38)	(−12.57)	
6	8.712***	−0.517***	47.44	7.823***	−0.554***	−0.346***	−0.156***	53.49
	(8.31)	(−83.63)		(7.90)	(−92.90)	(−26.24)	(−16.11)	
7	10.201***	−0.508***	45.15	9.493***	−0.547***	−0.363***	−0.199***	52.47
	(9.46)	(−79.87)		(9.42)	(−90.09)	(−27.05)	(−20.18)	
8	10.155***	−0.518***	44.75	9.662***	−0.559***	−0.365***	−0.248***	53.13
	(9.16)	(−79.21)		(9.42)	(−90.35)	(−26.73)	(−24.73)	
9	11.388***	−0.507***	42.12	10.837***	−0.552***	−0.404***	−0.280***	52.41
	(9.94)	(−75.09)		(10.40)	(−87.82)	(−29.10)	(−27.51)	
High	11.461***	−0.411***	31.10	11.028***	−0.453***	−0.381***	−0.270***	41.48
	(9.72)	(−59.14)		(10.10)	(−68.87)	(−26.21)	(−25.35)	
High–Low	1.510	0.150***	4.20	2.495*	0.129***	−0.154***	−0.392***	15.71
	(1.10)	(18.45)		(1.92)	(16.45)	(−8.89)	(−30.91)	
TLS	22.500***	−0.008	−0.01	22.864***	−0.495***	−0.337***	−0.447***	10.99
	(12.40)	(−0.70)		(13.34)	(−4.79)	(−14.78)	(−26.64)	
Panel B: Value-weighted portfolios								
Low	6.233***	−0.553***	48.25	5.524***	−0.551***	−0.003	0.167***	49.94
	(5.64)	(−84.99)		(5.07)	(−83.95)	(−0.18)	(15.71)	
2	5.734***	−0.557***	51.43	5.199***	−0.568***	−0.097***	0.013	51.87
	(5.49)	(−90.58)		(4.99)	(−90.31)	(−7.01)	(1.30)	
3	5.699***	−0.526***	48.87	5.408***	−0.537***	−0.080***	−0.031***	49.34
	(5.49)	(−86.05)		(5.21)	(−85.81)	(−5.78)	(−3.08)	
4	5.418***	−0.556***	49.14	5.175***	−0.575***	−0.151***	−0.112***	50.75
	(4.97)	(−86.53)		(4.80)	(−88.45)	(−10.56)	(−10.64)	
5	6.093***	−0.563***	48.85	6.104***	−0.577***	−0.097***	−0.115***	50.08
	(5.48)	(−86.02)		(5.54)	(−86.82)	(−6.62)	(−10.65)	
6	6.054***	−0.547***	47.17	6.229***	−0.565***	−0.118***	−0.183***	49.81
	(5.42)	(−83.17)		(5.70)	(−85.71)	(−8.14)	(−17.08)	
7	8.418***	−0.550***	46.23	8.534***	−0.571***	−0.161***	−0.205***	49.53
	(7.36)	(−81.61)		(7.67)	(−85.15)	(−10.91)	(−18.89)	
8	7.449***	−0.556***	45.88	7.868***	−0.578***	−0.156***	−0.272***	50.77
	(6.40)	(−81.05)		(7.06)	(−85.95)	(−10.51)	(−24.98)	
9	10.157***	−0.544***	42.37	10.312***	−0.577***	−0.258***	−0.322***	49.97
	(8.30)	(−75.48)		(9.01)	(−83.63)	(−16.97)	(−28.76)	
High	9.274***	−0.495***	34.86	9.605***	−0.528***	−0.271***	−0.374***	44.28
	(7.11)	(−64.40)		(7.94)	(−72.34)	(−16.82)	(−31.62)	
High–Low	3.045**	0.058***	0.51	4.082***	0.024***	−0.268***	−0.541***	19.58
	(1.97)	(6.39)		(2.93)	(2.80)	(−14.48)	(−39.76)	
TLS	17.400***	−0.047***	0.19	17.800***	−0.106***	−0.481***	−0.617***	17.27
	(8.58)	(−3.97)		(9.63)	(−9.55)	(−19.57)	(−34.15)	

Table 3
The components of the moving average strategies. We first divide the time series of MA timing portfolio j into two groups depending on whether a buying signal or a selling signal was issued by the MA rule, i.e. $P_{j,t-1} > A_{j,t-1}$ or $P_{j,t-1} \leq A_{j,t-1}$. We then calculate proportions of portfolio returns greater and smaller than the risk-free rate on the following day for both equally- and value-weighted portfolios. We perform the Chi-square test for equal proportions between the two groups. Numbers reported in parentheses are p-statistics.

Rank	Condition	Equally-weighted				Value-weighted			
		$R_p > R_f$	$R_p \leq R_f$	X^2	p-Value	$R_p > R_f$	$R_p \leq R_f$	X^2	p-Value
Low	$P_{j,t-1} > A_{j,t-1}$	57.14%	42.86%	81.96	(0.000)	53.32%	46.68%	17.67	(0.000)
	$P_{j,t-1} \leq A_{j,t-1}$	46.53%	53.47%	18.00	(0.000)	47.07%	52.93%	12.81	(0.000)
2	$P_{j,t-1} > A_{j,t-1}$	57.36%	42.64%	92.31	(0.000)	53.59%	46.41%	21.91	(0.000)
	$P_{j,t-1} \leq A_{j,t-1}$	47.79%	52.21%	6.80	(0.009)	48.29%	51.71%	4.11	(0.043)
3	$P_{j,t-1} > A_{j,t-1}$	57.56%	42.44%	99.39	(0.000)	53.70%	46.30%	23.73	(0.000)
	$P_{j,t-1} \leq A_{j,t-1}$	47.77%	52.23%	6.79	(0.009)	49.03%	50.97%	1.28	(0.258)
4	$P_{j,t-1} > A_{j,t-1}$	57.67%	42.33%	97.42	(0.000)	53.83%	46.17%	24.23	(0.000)
	$P_{j,t-1} \leq A_{j,t-1}$	47.03%	52.97%	12.69	(0.000)	49.35%	50.65%	0.61	(0.435)
5	$P_{j,t-1} > A_{j,t-1}$	57.96%	42.04%	107.34	(0.000)	54.10%	45.90%	28.19	(0.000)
	$P_{j,t-1} \leq A_{j,t-1}$	48.48%	51.52%	3.26	(0.071)	50.01%	49.99%	0.00	(0.987)
6	$P_{j,t-1} > A_{j,t-1}$	57.33%	42.67%	89.83	(0.000)	53.73%	46.27%	23.22	(0.000)
	$P_{j,t-1} \leq A_{j,t-1}$	47.95%	52.05%	5.98	(0.015)	48.16%	51.84%	4.86	(0.027)
7	$P_{j,t-1} > A_{j,t-1}$	57.77%	42.23%	98.66	(0.000)	54.79%	45.21%	37.37	(0.000)
	$P_{j,t-1} \leq A_{j,t-1}$	46.61%	53.39%	16.80	(0.000)	46.97%	53.03%	13.52	(0.000)
8	$P_{j,t-1} > A_{j,t-1}$	57.99%	42.01%	104.14	(0.000)	53.99%	46.01%	26.07	(0.000)
	$P_{j,t-1} \leq A_{j,t-1}$	46.77%	53.23%	15.33	(0.000)	47.56%	52.44%	8.69	(0.003)
9	$P_{j,t-1} > A_{j,t-1}$	57.43%	42.57%	89.95	(0.000)	56.22%	43.78%	62.30	(0.000)
	$P_{j,t-1} \leq A_{j,t-1}$	45.65%	54.35%	27.84	(0.000)	46.75%	53.25%	15.75	(0.000)
High	$P_{j,t-1} > A_{j,t-1}$	57.38%	42.62%	86.45	(0.000)	54.46%	45.54%	31.49	(0.000)
	$P_{j,t-1} \leq A_{j,t-1}$	45.46%	54.54%	31.17	(0.000)	46.99%	53.01%	13.72	(0.000)

We then follow Han et al. (forthcoming) in constructing the MA timing strategies. Let $P_{j,t}$ be denoted as the index price of portfolio j on day t. The L-day MA indicator of portfolio j on day t is defined as:

$$A_{j,t,L} \equiv \frac{P_{j,t-L+1} + P_{j,t-L+2} + \ldots + P_{j,t-1} + P_{j,t}}{L}, \tag{1}$$

which is the average price of the past L days. In this paper, 10-day MA is the main indicator examined. Nevertheless, 5-, 20-, 50-, 100-, and 200-day MAs are also investigated to consider different short-term and long-term effects. A simple trading rule based on the constructed MA indicator is to invest in the decile portfolio j, if the last closing price $P_{j,t-1}$ is above $A_{j,t-1,L}$ on trading day t; and to invest in the risk-free asset, otherwise. As a result, returns on the MA timing strategy for portfolio j can be described as follows:

$$\widetilde{R}_{j,t,L} = \begin{cases} R_{j,t}, & \text{if } P_{j,t-1} > A_{j,t-1,L}; \\ R_{f,t}, & \text{otherwise}, \end{cases} \tag{2}$$

where $R_{j,t}$ is the return of portfolio j on day t, and $R_{f,t}$ is the risk-free rate. To examine whether the MA timing strategy outperforms the standard buy-and-hold strategy, the difference between $\widetilde{R}_{j,t,L}$ and $R_{j,t}$, named as the MA portfolio return (MAP) hereafter, is computed for each of the 10 BM decile portfolios as follows:

$$MAP_{j,t,L} = \widetilde{R}_{j,t,L} - R_{j,t}, \qquad j = 1, \ldots, 10. \tag{3}$$

If the MA timing strategy does outperform the standard buy-and-hold strategy, we should expect positive MAPs. To further examine whether MAPs exhibit abnormal returns, we perform time-series regressions of the MAPs on the market portfolio, and on Fama–French three factors as follows:

$$MAP_{j,t,L} = \alpha_{j,L} + \beta_{j,L,MKT} R_{MKT,t} + \varepsilon_{j,t,L}, \tag{4}$$

Table 4

Average returns and Fama–French alphas of MAPs adjusting for exchange rates. We convert prices and returns into U.S. dollars, and calculate the returns of the MAPs formed from the 10-day MA timing strategy. We perform the time-series regressions of the MAPs formed from the 10-day MA timing strategy on Taiwan's Fama–French (1993) factors and U.S. Fama–French (1993) factors, respectively. The average returns, alphas, betas and the adjusted R^2 are reported; in parentheses are Newey and West's (1987) *t*-statistics. The average returns and alphas are in basis points. Panel A reports the results of equally-weighted portfolios, while Panel B reports the results of value-weighted portfolios. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Rank	Raw returns	Taiwan Fama–French model					U.S. Fama–French model				
		α	β_{MKT}	β_{SMB}	β_{HML}	Adj. R^2	α	β_{MKT}	β_{SMB}	β_{HML}	Adj. R^2
Panel A: Equally-weighted portfolios											
Low	13.360***	13.800***	−0.580***	−0.443***	−0.058***	51.99	14.400***	−0.059 ***	−0.099***	−0.009	0.28
	(7.39)	(12.89)	(−89.80)	(−31.17)	(−5.54)		(8.78)	(−3.76)	(−3.39)	(−0.29)	
2	9.650***	10.300***	−0.568***	−0.393***	−0.066***	51.88	10.900***	−0.074 ***	−0.112***	−0.016	0.45
	(5.78)	(9.84)	(−89.94)	(−28.34)	(−6.52)		(6.80)	(−4.84)	(−3.90)	(−0.54)	
3	7.950***	8.665***	−0.562***	−0.381***	−0.076***	52.27	9.035***	−0.068 ***	−0.101***	−0.016	0.37
	(4.97)	(8.43)	(−90.65)	(−27.93)	(−7.57)		(5.68)	(−4.47)	(−3.58)	(−0.52)	
4	8.250***	8.849***	−0.547***	−0.388***	−0.078***	51.31	9.325***	−0.061 ***	−0.106***	−0.013	0.35
	(5.06)	(8.67)	(−88.75)	(−28.67)	(−7.83)		(6.01)	(−4.10)	(−3.82)	(−0.44)	
5	7.740***	8.595***	−0.540***	−0.350***	−0.108***	52.36	8.713***	−0.065 ***	−0.088***	−0.012	0.36
	(4.98)	(8.70)	(−90.64)	(−26.71)	(−11.18)		(5.74)	(−4.52)	(−3.27)	(−0.43)	
6	7.560***	8.685***	−0.532***	−0.311***	−0.124***	52.29	8.891***	−0.050 ***	−0.087***	−0.022	0.24
	(4.98)	(8.91)	(−90.51)	(−24.06)	(−13.04)		(5.94)	(−3.54)	(−3.27)	(−0.80)	
7	7.780***	8.792***	−0.533***	−0.335***	−0.133***	52.83	9.227***	−0.053 ***	−0.099***	−0.007	0.30
	(5.06)	(9.08)	(−91.24)	(−26.08)	(−14.08)		(6.17)	(−3.69)	(−3.70)	(−0.23)	
8	6.420***	7.593***	−0.526***	−0.304***	−0.149***	51.59	7.842***	−0.059 ***	−0.090***	−0.007	0.32
	(4.19)	(7.75)	(−88.89)	(−23.35)	(−15.63)		(5.24)	(−4.12)	(−3.37)	(−0.24)	
9	6.680***	7.965***	−0.511***	−0.275***	−0.161***	49.88	8.126***	−0.049 ***	−0.084***	−0.009	0.24
	(4.52)	(8.07)	(−85.71)	(−21.01)	(−16.75)		(5.48)	(−3.46)	(−3.19)	(−0.31)	
High	5.990***	7.173***	−0.479***	−0.294***	−0.172***	43.85	7.215***	−0.039 ***	−0.074***	−0.008	0.15
	(3.93)	(6.81)	(−75.39)	(−21.02)	(−16.77)		(4.80)	(−2.73)	(−2.76)	(−0.27)	

High–Low	−7.400***	−6.633***	0.101***	0.149***	−0.114***	5.11	−7.181***	0.020 *	0.025	0.001	0.01
	(−5.94)	(−6.13)	(15.48)	(10.38)	(−10.84)		(−5.96)	(1.71)	(1.17)	(0.06)	
TLS	16.450***	16.900***	−0.055***	0.017	−0.069***	0.51	16.500***	−0.007	−0.046	−0.006	0.00
	(8.43)	(9.35)	(−4.99)	(0.73)	(−3.91)		(8.52)	(−0.38)	(−1.34)	(−0.16)	
Panel B: Value-weighted portfolios											
Low	8.550***	9.481***	−0.596***	−0.306***	−0.030***	50.37	9.531***	−0.072 ***	−0.110***	−0.004	0.39
	(4.72)	(8.44)	(−87.91)	(−20.51)	(−2.70)		(5.62)	(−4.48)	(−3.65)	(−0.13)	
2	6.240***	7.665***	−0.574***	−0.187***	−0.047***	49.62	6.987***	−0.079 ***	−0.143***	0.020	0.64
	(3.77)	(6.97)	(−86.48)	(−12.80)	(−4.39)		(4.23)	(−5.05)	(−4.86)	(0.64)	
3	5.660***	7.167***	−0.570***	−0.179***	−0.071***	49.81	6.198***	−0.078 ***	−0.141***	−0.021	0.56
	(3.62)	(6.58)	(−86.70)	(−12.37)	(−6.71)		(3.77)	(−5.00)	(−4.81)	(−0.68)	
4	5.770***	7.005***	−0.569***	−0.252***	−0.075***	49.70	6.307***	−0.069 ***	−0.098***	−0.025	0.34
	(3.45)	(6.44)	(−86.64)	(−17.48)	(−7.04)		(3.85)	(−4.41)	(−3.35)	(−0.83)	
5	4.970***	6.656***	−0.562***	−0.157***	−0.094***	49.88	5.784***	−0.088 ***	−0.128***	−0.021	0.61
	(3.15)	(6.18)	(−86.57)	(−10.98)	(−8.95)		(3.58)	(−5.69)	(−4.45)	(−0.69)	
6	5.440***	7.384***	−0.564***	−0.123***	−0.115***	50.86	6.806***	−0.083 ***	−0.138***	−0.053 *	0.59
	(3.40)	(6.94)	(−87.90)	(−8.69)	(−11.05)		(4.20)	(−5.40)	(−4.77)	(−1.75)	
7	6.240***	8.258***	−0.565***	−0.154***	−0.159***	50.60	7.470***	−0.077 ***	−0.137***	−0.034	0.52
	(3.98)	(7.69)	(−87.11)	(−10.78)	(−15.23)		(4.57)	(−4.93)	(−4.69)	(−1.11)	
8	5.330***	7.387***	−0.563***	−0.161***	−0.189***	51.26	6.590***	−0.085 ***	−0.110***	−0.027	0.53
	(3.35)	(6.95)	(−87.83)	(−11.42)	(−18.27)		(4.08)	(−5.53)	(−3.82)	(−0.88)	
9	5.130***	7.404***	−0.539***	−0.089***	−0.188***	46.94	6.377***	−0.061 ***	−0.135***	−0.015	0.41
	(3.33)	(6.64)	(−80.02)	(−5.98)	(−17.27)		(3.90)	(−3.89)	(−4.62)	(−0.51)	
High	5.030***	7.477***	−0.526***	−0.097***	−0.230***	45.08	6.226***	−0.069 ***	−0.103***	−0.017	0.36
	(3.05)	(6.55)	(−76.29)	(−6.38)	(−20.68)		(3.79)	(−4.40)	(−3.51)	(−0.55)	
High–Low	−3.500**	−2.010	0.070***	0.209***	−0.201***	4.94	−3.309**	0.004	0.008	−0.013	0.04
	(−2.21)	(−1.48)	(8.60)	(11.63)	(−15.19)		(−2.25)	(0.25)	(0.30)	(−0.46)	
TLS	10.630***	11.900***	−0.095***	0.048**	−0.190***	2.44	10.300***	−0.020	−0.037	0.005	0.00
	(5.44)	(6.51)	(19.18)	(1.98)	(−10.64)		(5.20)	(−1.07)	(−1.05)	(0.13)	

Table 5
Alternative moving average lag lengths of MAPs. This table reports the average returns (Panel A), the CAPM alphas (Panel B), and the Fama–French alphas (Panel C) of the MAPs when they are constructed based on 5-, 20-, 50-, 100- and 200-day moving average prices, respectively. The numbers are in basis points; in parentheses are Newey and West's (1987) *t*-statistics. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Rank	MAP(5)		MAP(20)		MAP(50)		MAP(100)		MAP(200)	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Panel A: Average returns										
Low	14.961***	9.741***	6.669***	4.096 **	4.702***	2.529	2.311	0.962	0.380	−0.073
	(8.20)	(5.79)	(3.96)	(2.55)	(2.63)	(1.52)	(1.29)	(0.59)	(0.21)	(−0.04)
2	11.629***	6.918***	5.682***	2.749 *	3.951**	1.221	2.438	0.337	0.180	−1.300
	(6.84)	(4.12)	(3.42)	(1.75)	(2.35)	(0.79)	(1.49)	(0.22)	(0.11)	(−0.86)
3	9.629***	5.744***	6.562***	3.993 ***	2.586	0.957	0.327	−0.113	−0.500	−0.600
	(6.09)	(3.64)	(4.25)	(2.74)	(1.64)	(0.65)	(0.21)	(−0.08)	(−0.34)	(−0.42)
4	10.094***	5.857***	5.232***	1.238	4.351**	1.129	2.845*	−0.131	1.830	−0.500
	(6.20)	(3.60)	(3.20)	(0.77)	(2.58)	(0.72)	(1.72)	(−0.08)	(1.06)	(−0.32)
5	9.350***	5.928***	5.868***	3.079 *	3.356**	1.874	0.914	−0.952	−0.700	−2.700
	(5.93)	(3.76)	(3.61)	(1.87)	(2.08)	(1.17)	(0.56)	(−0.60)	(−0.37)	(−1.58)
6	9.039***	5.727***	6.431***	3.781 **	4.057**	2.368	1.849	1.100	1.090	−1.000
	(6.07)	(3.69)	(4.15)	(2.48)	(2.54)	(1.60)	(1.22)	(0.75)	(0.73)	(−0.62)
7	9.429***	5.143***	7.221***	6.341 ***	4.201**	3.060*	1.598	0.149	0.520	−0.200
	(6.15)	(3.46)	(4.41)	(3.80)	(2.55)	(1.83)	(0.98)	(0.09)	(0.31)	(−0.13)
8	7.720***	4.881***	6.787***	4.484 ***	3.523**	2.765*	1.396	0.615	0.180	−0.200
	(5.14)	(3.30)	(3.95)	(2.62)	(2.01)	(1.67)	(0.84)	(0.38)	(0.11)	(−0.10)
9	7.888***	4.964***	7.730***	6.917 ***	5.698***	4.317**	3.940**	3.164 *	1.390	1.190
	(5.39)	(3.34)	(4.39)	(3.99)	(3.17)	(2.44)	(2.29)	(1.89)	(0.77)	(0.69)
High	7.484***	5.743***	9.416***	7.207 ***	7.839***	5.929***	4.753***	1.723	3.500**	0.170
	(5.00)	(3.67)	(5.50)	(3.87)	(4.53)	(3.27)	(2.77)	(0.93)	(2.06)	(0.09)
High–Low	−7.400***	−3.100*	2.750*	3.110 *	3.140*	3.400*	2.440	0.760	3.130*	0.240
	(−5.97)	(−1.96)	(1.73)	(1.80)	(1.88)	(1.94)	(1.41)	(0.42)	(1.71)	(0.13)
TLS	19.690***	13.070***	21.070***	17.240 ***	17.530***	14.400***	12.050***	8.620 ***	8.870***	6.040**
	(10.23)	(6.91)	(10.17)	(7.46)	(8.24)	(6.26)	(5.60)	(3.58)	(4.03)	(2.45)
Panel B: CAPM α										
Low	17.100***	12.000***	8.927***	6.338 ***	7.010***	4.803***	4.580***	3.206 ***	2.717**	2.189**
	(15.15)	(10.67)	(8.03)	(5.77)	(6.29)	(4.39)	(4.09)	(2.92)	(2.39)	(1.99)
2	13.800***	9.164***	7.953***	5.027 ***	6.111***	3.354***	4.467***	2.404 **	1.979*	0.542
	(12.65)	(8.28)	(7.44)	(4.79)	(5.69)	(3.18)	(4.19)	(2.28)	(1.87)	(0.52)
3	11.700***	7.990***	8.681***	6.136 ***	4.650***	3.065***	2.311**	1.927 *	1.326	1.337
	(10.93)	(7.18)	(8.37)	(5.92)	(4.51)	(2.95)	(2.24)	(1.86)	(1.29)	(1.31)
4	12.100***	8.019***	7.390***	3.483 ***	6.502***	3.322***	4.872***	1.986 *	3.827***	1.565
	(11.40)	(7.36)	(6.84)	3.18	(6.07)	(3.05)	(4.59)	(1.83)	(3.64)	(1.46)
5	11.400***	8.144***	7.994***	5.377 ***	5.408***	4.108***	2.976***	1.286	1.414	−0.306
	(11.00)	(7.45)	(7.61)	(4.82)	(5.18)	(3.70)	(2.86)	(1.16)	(1.35)	(−0.27)
6	11.000***	7.925***	8.555***	5.980 ***	6.112***	4.456***	3.717***	3.104 ***	2.895***	1.142
	(10.84)	(7.33)	(8.13)	(5.39)	(5.84)	(4.08)	(3.59)	(2.83)	(2.83)	(1.04)
7	11.400***	7.295***	9.303***	8.598 ***	6.262***	5.291***	3.572***	2.316 **	2.529**	1.882*
	(11.19)	(6.64)	(8.67)	(7.55)	(5.83)	(4.64)	(3.35)	(2.02)	(2.37)	(1.67)
8	9.704***	7.011***	8.934***	6.725 ***	5.649***	4.975***	3.327***	2.722 **	2.027*	1.896
	(9.47)	(6.50)	(8.05)	(5.80)	(5.10)	(4.36)	(3.02)	(2.37)	(1.85)	(1.64)
9	9.862***	7.072***	9.784***	9.184 ***	7.736***	6.498***	5.877***	5.184 ***	3.353***	3.281***
	(9.58)	(6.19)	(8.51)	(7.55)	(6.77)	(5.41)	(5.19)	(4.35)	(2.95)	(2.74)
High	9.249***	7.804***	11.100***	9.287 ***	9.475***	7.927***	6.249***	3.560 ***	4.821***	1.930
	(8.43)	(6.68)	(9.47)	(7.19)	(8.13)	(6.23)	(5.41)	(2.79)	(4.16)	(1.47)
High–Low	−7.753***	−3.269**	2.222	2.953 *	2.469*	3.128**	1.669	0.353	2.106	−0.257
	(−7.06)	(−2.34)	(1.63)	(1.94)	(1.81)	(2.09)	(1.21)	(0.23)	(1.46)	(−0.16)
TLS	19.800***	13.300***	21.100***	17.500 ***	17.500***	14.600***	11.900***	8.613 ***	8.583***	5.969***
	(10.99)	(7.23)	(11.63)	(8.66)	(9.80)	(7.28)	(6.69)	(4.34)	(4.95)	(3.00)
Panel C: Fama–French α										
Low	15.700***	11.000***	7.453***	5.557 ***	5.463***	4.077***	3.165***	2.471 **	0.965	1.193
	(14.70)	(9.84)	(6.86)	(5.13)	(5.04)	(3.78)	(2.89)	(2.29)	(0.88)	(1.11)
2	12.500***	8.498***	6.522***	4.405 ***	4.878***	2.889***	3.538***	2.090 **	1.122	0.232
	(12.10)	(7.70)	(6.27)	(4.20)	(4.65)	(2.75)	(3.36)	(1.99)	(1.07)	(0.22)

Table 5 *(continued)*

Rank	MAP(5)		MAP(20)		MAP(50)		MAP(100)		MAP(200)	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Panel C: Fama–French α										
3	10.500***	7.354***	7.490***	5.781 ***	3.574***	2.869***	1.205	1.728 *	0.068	1.097
	(10.32)	(6.62)	(7.44)	(5.58)	(3.56)	(2.76)	(1.19)	(1.66)	(0.07)	(1.07)
4	11.000***	7.303***	6.081***	3.132 **	5.115***	2.942***	3.618***	1.649	2.304**	1.131
	(10.86)	(6.76)	(5.93)	(2.90)	(5.02)	(2.73)	(3.53)	(1.53)	(2.28)	(1.06)
5	10.400***	7.796***	7.083***	5.312 ***	4.503***	4.230***	2.077**	1.364	0.330	−0.109
	(10.57)	(7.17)	(7.05)	(4.80)	(4.48)	(3.83)	(2.06)	(1.23)	(0.33)	(−0.10)
6	10.300***	7.865***	7.544***	5.909 ***	5.104***	4.476***	2.793***	3.104 ***	1.912*	1.152
	(10.63)	(7.30)	(7.57)	(5.42)	(5.13)	(4.14)	(2.80)	(2.85)	(1.93)	(1.06)
7	10.700***	7.325***	8.412***	8.600 ***	5.369***	5.299***	2.741***	2.309**	1.523	1.827*
	(11.10)	(6.76)	(8.38)	(7.75)	(5.33)	(4.75)	(2.71)	(2.05)	(1.52)	(1.65)
8	9.156***	7.132***	8.231***	6.826 ***	4.957***	4.976***	2.733***	3.049***	1.353	2.404**
	(9.39)	(6.76)	(8.02)	(6.12)	(4.84)	(4.48)	2.64	(2.73)	(1.32)	(2.14)
9	9.445***	7.498***	9.082***	9.295 ***	7.056***	6.475***	5.335***	5.275***	2.811***	3.541***
	(9.62)	(6.68)	(8.67)	(8.12)	(6.72)	(5.66)	(5.08)	(4.62)	(2.68)	(3.10)
High	8.828***	8.325***	10.600***	9.568 ***	8.903***	8.296***	5.842***	4.014***	4.819***	2.747**
	(8.40)	(7.27)	(9.76)	(7.95)	(8.20)	(6.95)	(5.39)	(3.35)	(4.39)	(2.25)
High–Low	−6.763	−1.636	3.189**	4.011 ***	3.440***	4.220***	2.677**	1.543	3.854***	1.554
	(−6.21)	(−1.19)	(2.49)	(2.91)	(2.67)	(3.10)	(2.06)	(1.21)	(2.84)	(1.11)
TLS	20.400***	14.500***	21.400***	17.800 ***	17.700***	15.000***	12.300***	9.142***	9.086***	6.597***
	(11.29)	(7.93)	(12.42)	(9.64)	(10.36)	(8.14)	(7.20)	(4.97)	(5.45)	(3.62)

$$MAP_{j,t,L} = \alpha_{j,L} + \beta_{j,L,MKT} R_{MKT,t} + \beta_{j,L,SMB} R_{SMB,t} + \beta_{j,L,HML} R_{HML,t} + \varepsilon_{j,t,L}, \tag{5}$$

where $R_{MKT,t}$ is the excess return on the market portfolio on day t, $R_{SMB,t}$ and $R_{HML,t}$ are returns on the SMB and HML factors on day t, respectively.[1] We follow the procedure of Fama and French (1993) in constructing daily returns of SMB and HML factors.

2.2. A zero-cost strategy based on moving averages

In discussing whether the MA timing strategy provides any useful information and increases portfolio return, Han et al. (forthcoming) suggest a simple difference between returns, $\widetilde{R}_{j,t,L}$, of the highest and the lowest volatility decile portfolios. This is fine with investment on volatility decile portfolios. However, for the value investing (buy high BM and short-sell low BM portfolios) examined in this paper, a simple difference between returns, $\widetilde{R}_{j,t,L}$, of the highest and the lowest BM decile portfolios implies that investors sell short the lowest BM portfolio when the index price is higher than its MA indicator, which is in contradiction to the spirit of MA signals. Therefore, in this paper, we propose an alternative zero-cost strategy by going long on the highest BM portfolio, and going short on the lowest BM portfolio conditioning on the trading signals implied by MAs. The return of such a MA timing strategy can be expressed as:

$$TLS_{MA,t,L} = \begin{cases} R_{10,t} - R_{1,t}, & \text{if } P_{10,t-1} > A_{10,t-1,L} \text{ and } P_{1,t-1} < A_{1,t-1,L}; \\ R_{10,t} - R_{f,t}, & \text{if } P_{10,t-1} > A_{10,t-1,L} \text{ and } P_{1,t-1} > A_{1,t-1,L}; \\ R_{f,t} - R_{1,t}, & \text{if } P_{10,t-1} < A_{10,t-1,L} \text{ and } P_{1,t-1} < A_{1,t-1,L}; \\ 0, & \text{otherwise}, \end{cases} \tag{6}$$

where $R_{10,t}$ ($R_{1,t}$) is the return of the highest (lowest) BM portfolio on day t, $P_{10,t-1}$ ($P_{1,t-1}$) is the index price of the highest (lowest) BM portfolio on day t, and $A_{10,t-1,L}$ ($A_{1,t-1,L}$) is the L-day MA indicator of the

[1] We use the TAIEX index, which contains all listed common stocks, and is a value-weighted index compiled by TWSE, as the proxy for the market portfolio.

Table 6

Average consecutive holding days, trading frequencies and break-even transaction costs. The table reports the average consecutive holding days (Holding), the fraction of trading days (Freq) and break-even transaction costs (BETC) of the MAPs when they are constructed by using 5-, 10-, 20-, 50-, 100- and 200-day MAs, respectively. The average consecutive holding days of High–Low and TLS strategies are recorded as n.a. because it is difficult to identify the holding days of the combination of two long and short positions. The break-even transaction costs for those portfolios with negative MAP returns are also reported as n.a. because negative cost is not applicable.

Rank	MAP(5)			MAP(10)			MAP(20)			MAP(50)			MAP(100)			MAP(200)		
	Holding	Freq	BETC	Holding	Freq	BETC	Holding	Freq	BETC	Holding	Freq	BETC	Holding	Freq	BETC	Holding	Freq	BETC
Panel A: Equally-weighted portfolios																		
Low	4.72	0.109	136.67	7.50	0.069	110.75	12.49	0.041	161.98	21.89	0.024	197.99	43.08	0.017	139.86	33.37	0.016	23.76
2	4.87	0.111	105.11	8.33	0.066	110.17	12.44	0.043	131.41	24.39	0.022	176.96	33.41	0.014	176.52	65.78	0.009	20.91
3	4.94	0.109	87.97	8.27	0.068	107.93	12.93	0.043	153.15	25.23	0.022	115.83	36.52	0.021	15.92	54.69	0.011	n.a.
4	5.27	0.104	97.04	8.18	0.065	122.57	11.90	0.044	119.24	24.83	0.021	204.30	38.49	0.016	179.20	55.25	0.011	170.43
5	5.09	0.108	86.66	8.17	0.067	102.16	12.17	0.045	131.78	22.04	0.025	135.42	31.07	0.017	53.24	53.12	0.011	n.a.
6	5.10	0.109	83.28	7.68	0.070	93.63	12.74	0.042	154.28	22.80	0.024	170.85	37.28	0.015	125.64	66.07	0.009	118.94
7	5.25	0.106	89.31	8.03	0.066	123.88	12.15	0.043	169.55	21.63	0.024	174.98	33.76	0.017	92.37	48.02	0.012	43.43
8	5.27	0.105	73.31	7.62	0.069	116.25	12.45	0.041	163.81	20.01	0.025	139.97	32.26	0.018	79.56	47.59	0.012	15.44
9	5.31	0.105	75.17	7.62	0.069	135.23	11.90	0.043	178.77	20.41	0.025	229.93	41.82	0.013	308.39	44.27	0.012	118.19
High	5.48	0.104	71.85	7.38	0.069	140.90	11.25	0.044	212.08	22.75	0.022	359.38	36.38	0.013	372.01	50.13	0.010	347.96
High–Low	n.a.	0.213	n.a.	n.a.	0.139	15.31	n.a.	0.086	32.10	n.a.	0.046	68.86	n.a.	0.029	83.38	n.a.	0.026	120.49
TLS	n.a.	0.213	92.51	n.a.	0.139	161.82	n.a.	0.086	246.24	n.a.	0.046	385.79	n.a.	0.029	413.11	n.a.	0.026	343.47
Panel B: Value-weighted portfolios																		
Low	4.27	0.117	80.03	7.14	0.072	54.85	11.38	0.046	89.16	18.51	0.029	87.88	39.24	0.021	45.71	40.32	0.014	n.a.
2	4.47	0.119	61.09	7.53	0.073	47.53	11.43	0.048	57.40	20.96	0.027	45.91	34.43	0.016	21.25	44.34	0.013	n.a.
3	4.55	0.117	47.23	7.65	0.073	48.43	12.12	0.047	85.45	21.45	0.027	35.99	36.25	0.018	n.a.	56.16	0.011	n.a.
4	4.86	0.113	60.72	7.65	0.070	45.23	10.94	0.048	25.57	21.68	0.025	46.05	34.80	0.015	n.a.	52.88	0.011	n.a.
5	4.67	0.116	47.66	7.59	0.071	53.15	11.93	0.046	67.58	23.58	0.023	79.76	27.05	0.017	n.a.	45.90	0.012	n.a.
6	4.82	0.114	54.24	7.35	0.073	51.85	12.04	0.045	83.46	21.60	0.026	92.66	29.34	0.016	69.89	42.74	0.013	n.a.
7	4.77	0.114	52.58	7.78	0.068	91.51	12.24	0.042	149.78	22.31	0.023	132.43	30.29	0.018	8.12	42.44	0.013	n.a.
8	4.81	0.114	51.33	7.46	0.071	72.95	12.16	0.043	103.71	20.85	0.025	112.75	26.32	0.015	42.17	49.76	0.011	n.a.
9	5.08	0.109	56.41	7.37	0.071	112.41	11.09	0.046	150.53	20.23	0.026	168.93	32.27	0.015	213.19	48.64	0.011	104.78
High	4.91	0.112	56.19	7.18	0.071	102.01	11.08	0.045	158.63	22.70	0.022	264.01	28.40	0.016	108.53	43.10	0.012	14.77
High–Low	n.a.	0.228	n.a.	n.a.	0.144	23.68	n.a.	0.091	36.35	n.a.	0.051	74.62	n.a.	0.037	25.99	n.a.	0.026	9.41
TLS	n.a.	0.228	57.23	n.a.	0.144	119.60	n.a.	0.091	188.69	n.a.	0.051	281.69	n.a.	0.037	234.43	n.a.	0.026	232.75

Table 7
Subperiod analysis on Fama–French alphas of 10-day MAPs. We perform the time-series regressions of the MAPs formed from the 10-day MA timing strategy on Fama and French's (1993) three-factor model for periods from July 1, 1982 to December 31, 1996 and from January 1, 1997 to December 31, 2010. The alphas, betas and the adjusted R^2 are reported; in parentheses are Newey and West's (1987) *t*-statistics. The alphas are in basis points. Panels A and B report the results of equally- and value-weighted portfolios. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Rank	1982/07/01–1996/12/31					1997/01/01–2010/12/31				
	α	β_{MKT}	β_{SMB}	β_{HML}	Adj. R^2	α	β_{MKT}	β_{SMB}	β_{HML}	Adj. R^2
Panel A: Equally-weighted portfolios										
Low	9.269***	−0.530***	−0.139***	0.148***	50.47	6.160***	−0.736***	−0.506***	0.087***	56.39
	(6.25)	(−64.34)	(−7.41)	(9.36)		(4.08)	(−64.95)	(−21.35)	(6.34)	
2	8.867***	−0.517***	−0.240***	0.034**	48.96	6.103***	−0.697***	−0.518***	−0.021*	57.74
	(5.89)	(−61.78)	(−12.59)	(2.14)		(4.49)	(−68.36)	(−24.26)	(−1.73)	
3	8.753***	−0.498***	−0.259***	−0.008	48.85	6.561***	−0.684***	−0.518***	−0.080***	58.33
	(5.98)	(−61.23)	(−13.96)	(−0.49)		(5.00)	(−69.54)	(−25.17)	(−6.78)	
4	9.017***	−0.517***	−0.360***	−0.061***	49.78	7.907***	−0.676***	−0.519***	−0.131***	58.64
	(5.91)	(−60.92)	(−18.59)	(−3.75)		(6.14)	(−69.96)	(−25.65)	(−11.24)	
5	8.771***	−0.521***	−0.255***	−0.076***	49.13	6.645***	−0.633***	−0.477***	−0.170***	58.03
	(5.74)	(−61.38)	(−13.17)	(−4.65)		(5.40)	(−68.66)	(−24.70)	(−15.30)	
6	7.989***	−0.534***	−0.297***	−0.102***	51.31	6.953***	−0.628***	−0.481***	−0.207***	59.06
	(5.28)	(−63.51)	(−15.49)	(−6.33)		(5.80)	(−69.75)	(−25.55)	(−19.03)	
7	10.800***	−0.533***	−0.320***	−0.133***	50.33	7.401***	−0.605***	−0.472***	−0.258***	58.11
	(6.98)	(−61.71)	(−16.25)	(−8.01)		(6.18)	(−67.41)	(−25.13)	(−23.82)	
8	9.062***	−0.538***	−0.317***	−0.175***	50.64	9.714***	−0.633***	−0.497***	−0.315***	59.44
	(5.78)	(−61.72)	(−15.94)	(−10.48)		(7.86)	(−68.28)	(−25.61)	(−28.18)	
9	10.000***	−0.529***	−0.378***	−0.196***	50.22	11.200***	−0.622***	−0.501***	−0.359***	58.10
	(6.34)	(−60.06)	(−18.83)	(−11.64)		(8.83)	(−65.21)	(−25.05)	(−31.15)	
High	9.379***	−0.412***	−0.369***	−0.147***	37.13	12.200***	−0.562***	−0.495***	−0.390***	52.81
	(5.69)	(−44.95)	(−17.65)	(−8.38)		(9.27)	(−56.77)	(−23.87)	(−32.63)	
High-Low	0.110	0.119***	−0.229***	−0.295***	9.51	6.065***	0.174***	0.012	−0.476***	24.99
	(0.06)	(11.68)	(−9.91)	(−15.17)		(3.35)	(12.79)	(0.41)	(−29.04)	
TLS	21.500***	0.015	−0.423***	−0.344***	7.18	23.900***	−0.162***	−0.330***	−0.560***	20.67
	(8.43)	(1.06)	(−13.04)	(−12.65)		(11.03)	(−9.97)	(−9.69)	(−28.50)	
Panel B: Value-weighted portfolios										
Low	8.805***	−0.529***	0.047**	0.211***	46.86	0.958	−0.629***	−0.147***	0.125***	55.56
	(5.54)	(−59.83)	(2.32)	(12.45)		(0.66)	(−58.22)	(−6.51)	(9.63)	
2	5.889***	−0.528***	−0.110***	0.008	49.55	3.766***	−0.648***	−0.169***	0.005	55.97
	(3.94)	(−63.53)	(−5.79)	(0.47)		(2.65)	(−60.74)	(−7.56)	(0.36)	
3	6.501***	−0.482***	−0.090***	−0.028*	46.43	3.220**	−0.652***	−0.191***	−0.052***	54.89
	(4.47)	(−59.58)	(−4.90)	(−1.83)		(2.23)	(−60.23)	(−8.44)	(−4.00)	
4	6.144***	−0.531***	−0.180***	−0.111***	49.39	3.464**	−0.656***	−0.203***	−0.129***	53.79
	(4.00)	(−62.15)	(−9.21)	(−6.75)		(2.34)	(−59.20)	(−8.75)	(−9.64)	
5	7.391***	−0.523***	−0.119***	−0.103***	48.24	3.804**	−0.685***	−0.184***	−0.143***	54.06
	(4.80)	(−61.15)	(−6.11)	(−6.30)		(2.46)	(−59.01)	(−7.56)	(−10.22)	
6	7.714***	−0.522***	−0.099***	−0.144***	47.00	3.602**	−0.673***	−0.256***	−0.229***	55.49
	(4.88)	(−59.32)	(−4.93)	(−8.56)		(2.47)	(−61.54)	(−11.20)	(−17.32)	
7	9.761***	−0.534***	−0.174***	−0.127***	46.88	6.577***	−0.655***	−0.225***	−0.285***	55.20
	(5.99)	(−59.00)	(−8.42)	(−7.32)		(4.52)	(−60.01)	(−9.85)	(−21.66)	
8	7.449***	−0.542***	−0.116***	−0.192***	48.23	7.494***	−0.683***	−0.310***	−0.351***	56.52
	(4.60)	(−60.19)	(−5.66)	(−11.16)		(5.09)	(−61.83)	(−13.40)	(−26.34)	
9	9.033***	−0.542***	−0.219***	−0.234***	48.20	11.000***	−0.680***	−0.408***	−0.407***	54.60
	(5.47)	(−59.03)	(−10.46)	(−13.29)		(7.18)	(−51.39)	(−17.02)	(−29.46)	
High	8.734***	−0.487***	−0.245***	−0.268***	42.20	9.782***	−0.640***	−0.411***	−0.477***	49.62
	(5.09)	(−51.00)	(−11.24)	(−14.67)		(5.92)	(−51.69)	(−15.86)	(−31.92)	
High–Low	−0.072	0.042***	−0.291***	−0.479***	14.03	8.882***	−0.012	−0.264***	−0.603***	26.28
	(−0.04)	(3.92)	(−11.90)	(−23.30)		(4.41)	(−0.77)	(−8.40)	(−33.29)	
TLS	20.000***	−0.013	−0.551***	−0.604***	14.09	14.000***	−0.279***	−0.575***	−0.661***	25.56
	(7.37)	(−0.89)	(−15.99)	(−20.88)		(5.85)	(−15.54)	(−15.31)	(−30.55)	

Table 8
Business cycles and 10-day MAP returns. We perform the time-series regressions of the MAPs formed from the 10-day MA timing strategy on Fama and French's (1993) three-factor model and two dummy variables on good and bad states for period from July 1, 1982 to December 31, 2010. The alphas, betas and the adjusted R^2 are reported; in parentheses are Newey and West's (1987) *t*-statistics. The alphas are in basis points. Panels A and B report the results of equally- and value-weighted portfolios. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Rank	Good and bad states are identified by GDP growth							Good and bad states are identified by past three-year market returns					
	α	β_{MKT}	β_{SMB}	β_{HML}	β_{Good}	β_{Bad}	Adj. R^2	α	β_{MKT}	β_{SMB}	β_{HML}	β_{Bad}	Adj. R^2
Panel A: Equally-weighted portfolios													
Low	10.100***	−0.582***	−0.228***	0.122***	−2.904	−1.779	51.56	19.10***	−0.634***	−0.353***	0.094*	−18.900*	55.80
	(4.69)	(−89.55)	(−15.86)	(11.58)	(−0.94)	(−0.67)		(3.18)	(−20.51)	(−4.87)	(1.81)	(−1.77)	
2	8.068***	−0.565***	−0.299***	0.011	2.006	−0.761	51.38	15.50***	−0.594***	−0.360***	−0.008	−22.000**	53.48
	(3.87)	(−90.17)	(−21.66)	(1.09)	(0.68)	(−0.30)		(2.63)	(−19.55)	(−5.04)	(−0.16)	(−2.10)	
3	8.460***	−0.548***	−0.309***	−0.039***	−0.768	0.073	51.43	8.583	−0.627***	−0.460***	−0.040	−2.086	58.77
	(4.18)	(−90.28)	(−23.06)	(−3.97)	(−0.27)	(0.03)		(1.53)	(−21.72)	(−6.79)	(−0.82)	(−0.21)	
4	9.266***	−0.563***	−0.378***	−0.091***	0.181	−0.734	52.31	15.000***	−0.637***	−0.389***	−0.175***	−6.013	60.44
	(4.51)	(−91.28)	(−27.73)	(−9.08)	(0.06)	(−0.29)		(2.71)	(−22.36)	(−5.82)	(−3.67)	(−0.61)	
5	5.469***	−0.546***	−0.312***	−0.124***	5.736 **	2.568	51.67	15.100***	−0.619***	−0.404***	−0.113**	−14.700	59.63
	(2.70)	(−89.99)	(−23.32)	(−12.62)	(2.00)	(1.04)		(2.77)	(−22.03)	(−6.13)	(−2.40)	(−1.52)	
6	7.288***	−0.554***	−0.346***	−0.156***	2.271	−0.035	53.49	15.300***	−0.630***	−0.409***	−0.159***	−11.300	59.73
	(3.66)	(−92.82)	(−26.22)	(−16.12)	(0.80)	(−0.01)		(2.75)	(−22.00)	(−6.08)	(−3.31)	(−1.14)	
7	8.046***	−0.547***	−0.363***	−0.199***	2.292	1.748	52.47	18.500***	−0.616***	−0.384***	−0.139***	−23.000**	57.01
	(3.97)	(−90.01)	(−27.01)	(−20.19)	(0.80)	(0.71)		(3.22)	(−20.77)	(−5.51)	(−2.79)	(−2.24)	
8	9.382***	−0.558***	−0.365***	−0.248***	1.735	−0.281	53.12	16.600***	−0.640***	−0.437***	−0.261***	−13.600	61.98
	(4.55)	(−90.27)	(−26.71)	(−24.73)	(0.59)	(−0.11)		(3.03)	(−22.59)	(−6.57)	(−5.49)	(−1.39)	
9	8.484***	−0.551***	−0.403***	−0.281***	5.106 *	2.181	52.42	19.900***	−0.596***	−0.357***	−0.275***	−18.300*	54.88
	(4.05)	(−87.73)	(−29.05)	(−27.55)	(1.72)	(0.85)		(3.34)	(−19.43)	(−4.95)	(−5.35)	(−1.72)	
High	11.700***	−0.453***	−0.381***	−0.270***	0.148	−1.414	41.47	9.098	−0.467***	−0.355***	−0.289***	−6.626	46.66
	(5.34)	(−68.82)	(−26.21)	(−25.33)	(0.05)	(−0.53)		(1.61)	(−15.98)	(−5.18)	(−5.90)	(−0.66)	
High–Low	1.566	0.129***	−0.153***	−0.393***	3.052	0.365	15.70	−9.961	0.167***	−0.002	−0.383***	12.300	14.19
	(0.60)	(16.47)	(−8.88)	(−30.92)	(0.82)	(0.11)		(−1.40)	(4.53)	(−0.02)	(−6.21)	(0.96)	

TLS	24.300***	−0.050***	−0.338***	−0.446***	−2.779	−1.469	10.97	30.100***	−0.135***	−0.305***	−0.497***	−18.000	13.04
	(7.05)	(−4.80)	(−14.79)	(−26.61)	(−0.57)	(−0.35)		(3.31)	(−2.87)	(−2.77)	(−6.31)	(−1.11)	
Rank	Market states identified by GDP growth							Market states identified by market returns					
	α	β_{MKT}	β_{SMB}	β_{HML}	β_{Good}	β_{Bad}	Adj. R^2	α	β_{MKT}	β_{SMB}	β_{HML}	β_{Bad}	Adj. R^2
Panel B: Value-weighted portfolios													
Low	6.435***	−0.551***	−0.003	0.168***	−2.380	−0.652	49.93	15.500**	−0.601***	−0.019	0.157***	−10.100	52.50
	(2.94)	(−83.92)	(−0.19)	(15.73)	(−0.77)	(−0.24)		(2.55)	(−19.12)	(−0.26)	(2.98)	(−0.93)	
2	6.411***	−0.568***	−0.098***	0.013	−0.435	−2.176	51.86	12.200**	−0.599***	−0.239***	0.021	−12.300	52.37
	(3.06)	(−90.26)	(−7.03)	(1.31)	(−0.15)	(−0.85)		(2.04)	(−19.37)	(−3.30)	(0.40)	(−1.15)	
3	4.303**	−0.537***	−0.080***	−0.031***	−0.474	2.399	49.34	7.780	−0.644***	−0.097	−0.032	1.349	56.72
	(2.06)	(−85.78)	(−5.76)	(−3.08)	(−0.16)	(0.94)		(1.32)	(−21.17)	(−1.36)	(−0.62)	(0.13)	
4	5.940***	−0.575***	−0.152***	−0.112***	−0.271	−1.374	50.74	4.070	−0.608***	−0.156**	−0.206***	−5.048	54.88
	(2.74)	(−88.39)	(−10.56)	(−10.63)	(−0.09)	(−0.52)		(0.69)	(−20.00)	(−2.18)	(−4.05)	(−0.48)	
5	3.039	−0.577***	−0.096***	−0.115***	5.693 *	3.299	50.08	15.200**	−0.650***	−0.077	−0.141***	−15.200	57.93
	(1.37)	(−86.73)	(−6.57)	(−10.70)	(1.81)	(1.22)		(2.59)	(−21.40)	(−1.08)	(−2.76)	(−1.45)	
6	5.730***	−0.565***	−0.118***	−0.183***	0.763	0.614	49.80	14.700**	−0.640***	−0.178**	−0.170***	−18.400*	54.92
	(2.61)	(−85.65)	(−8.12)	(−17.07)	(0.24)	(0.23)		(2.37)	(−20.08)	(−2.38)	(−3.18)	(−1.67)	
7	6.802***	−0.571***	−0.161***	−0.206***	3.955	1.512	49.53	14.900**	−0.628***	−0.160**	−0.229***	−10.600	55.85
	(3.04)	(−85.06)	(−10.88)	(−18.92)	(1.25)	(0.56)		(2.49)	(−20.30)	(−2.21)	(−4.41)	(−0.99)	
8	6.503***	−0.578***	−0.156***	−0.273***	3.410	1.050	50.76	16.800***	−0.633***	−0.252***	−0.291***	−20.700**	58.00
	(2.90)	(−85.87)	(−10.49)	(−25.00)	(1.07)	(0.38)		(2.85)	(−20.82)	(−3.53)	(−5.71)	(−1.97)	
9	8.281***	−0.577***	−0.258***	−0.322***	3.038	2.538	49.97	18.500***	−0.598***	−0.232***	−0.318***	−10.700	53.25
	(3.60)	(−83.55)	(−16.93)	(−28.77)	(0.93)	(0.91)		(3.00)	(−18.78)	(−3.11)	(−5.96)	(−0.97)	
High	12.300***	−0.528***	−0.272***	−0.373***	−5.298	−2.833	44.29	8.521	−0.599***	−0.176**	−0.448***	−6.221	49.98
	(5.07)	(−72.35)	(−16.85)	(−31.55)	(−1.54)	(−0.96)		(1.24)	(−16.89)	(−2.11)	(−7.54)	(−0.51)	
High–Low	5.902**	0.023***	−0.269***	−0.541***	−2.918	−2.181	19.56	−7.025	0.002	−0.157	−0.605***	3.889	17.49
	(2.11)	(2.78)	(−14.49)	(−39.72)	(−0.73)	(−0.64)		(−0.86)	(0.05)	(−1.59)	(−8.59)	(0.27)	
TLS	19.600***	−0.107***	−0.481***	−0.616***	−7.658	0.021	17.29	26.300**	−0.215***	−0.396***	−0.752***	−23.000	21.70
	(5.29)	(−9.60)	(−19.58)	(−34.10)	(−1.45)	(0.00)		(2.58)	(−4.08)	(−3.21)	(−8.53)	(−1.27)	

Table 9

Market timing of 10-day MAPs. We perform Treynor and Mazuy's (1966) quadratic regression and Henriksson and Merton's (1981) regression of the MAPs formed from the 10-day MA timing strategy, respectively. The alphas, betas and the adjusted R^2 are reported; in parentheses are Newey and West's (1987) *t*-statistics. The alphas are in basis points. Panels A and B report the results of equally- and value-weighted portfolios. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Rank	TM regression				HM regression			
	α	β_{MKT}	β_{MKT^2}	Adj. R^2	α	β_{MKT}	γ_{MKT}	Adj. R^2
Panel A: Equally-weighted portfolios								
Low	7.504***	−0.559***	0.849***	49.24	−7.318***	−0.631***	33.700***	49.86
	(6.14)	(−86.30)	(4.59)		(−3.79)	(−69.05)	(10.84)	
2	7.126***	−0.534***	0.806***	48.46	−5.816***	−0.597***	29.800***	48.97
	(6.02)	(−84.96)	(4.49)		(−3.10)	(−67.34)	(9.88)	
3	6.791***	−0.515***	0.913***	48.03	−4.866***	−0.575***	27.900***	48.44
	(5.88)	(−84.15)	(5.22)		(−2.66)	(−66.45)	(9.48)	
4	7.334***	−0.523***	0.975***	47.05	−0.774	−0.569***	21.300***	47.19
	(6.14)	(−82.50)	(5.39)		(−0.41)	(−63.35)	(6.98)	
5	5.772***	−0.512***	1.093***	47.32	−3.077*	−0.562***	23.400***	47.48
	(4.96)	(−82.86)	(6.20)		(−1.66)	(−64.28)	(7.88)	
6	5.403***	−0.515***	1.141***	47.72	−3.652**	−0.567***	24.100***	47.88
	(4.65)	(−83.50)	(6.48)		(−1.98)	(−64.91)	(8.11)	
7	7.323***	−0.506***	1.001***	45.37	0.893	−0.546***	18.200***	45.40
	(6.12)	(−79.72)	(5.52)		(0.47)	(−60.60)	(5.94)	
8	7.336***	−0.516***	0.978***	44.94	−2.063	−0.567***	23.800***	45.15
	(5.96)	(−79.05)	(5.25)		(−1.06)	(−61.38)	(7.59)	
9	7.712***	−0.505***	1.275***	42.44	0.733	−0.550***	20.800***	42.42
	(6.07)	(−74.94)	(6.63)		(0.36)	(−57.56)	(6.40)	
High	7.437***	−0.409***	1.395***	31.53	6.580***	−0.431***	9.520***	31.16
	(5.69)	(−58.97)	(7.04)		(3.16)	(−43.69)	(2.84)	
High–Low	−0.007	0.150***	0.546**	4.25	13.900***	0.201***	−24.100***	4.66
	(−0.04)	(18.54)	(2.36)		(5.72)	(17.42)	(−6.19)	
TLS	16.900***	−0.005***	1.935***	0.50	12.900***	−0.046***	18.600***	0.15
	(8.40)	(−0.43)	(6.36)		(4.04)	(−3.06)	(3.62)	
Panel B: Value-weighted portfolios								
Low	4.439***	−0.552***	0.621***	48.32	−8.417***	−0.613***	28.600***	48.79
	(3.62)	(−84.82)	(3.34)		(−4.33)	(−66.67)	(9.15)	
2	3.149***	−0.556***	0.897***	51.59	−7.412***	−0.611***	25.600***	51.89
	(2.72)	(−90.42)	(5.11)		(−4.04)	(−70.26)	(8.68)	
3	3.302***	−0.525***	0.831***	49.01	−6.892***	−0.577***	24.500***	49.32
	(2.86)	(−85.89)	(4.76)		(−3.77)	(−66.81)	(8.36)	
4	3.420***	−0.555***	0.693***	49.23	−5.479***	−0.601***	21.200***	49.45
	(2.82)	(−86.36)	(3.78)		(−2.85)	(−66.00)	(6.87)	
5	3.174**	−0.562***	1.012***	49.03	−4.091**	−0.605***	19.900***	49.10
	(2.57)	(−85.86)	(5.42)		(−2.09)	(−65.21)	(6.30)	
6	4.238***	−0.546***	0.621***	47.24	−1.742	−0.579***	15.200***	47.32
	(3.42)	(−83.01)	(3.31)		(−0.88)	(−62.06)	(4.78)	
7	5.510***	−0.548***	1.010***	46.41	0.155	−0.584***	16.100***	46.39
	(4.34)	(−81.45)	(5.25)		(0.08)	(−61.10)	(4.97)	
8	5.682***	−0.555***	0.614***	45.94	−7.116***	−0.616***	28.400***	46.39
	(4.39)	(−80.88)	(3.13)		(−3.47)	(−63.47)	(8.62)	
9	6.617***	−0.542***	1.227***	42.63	2.738	−0.574***	14.500***	42.50
	(4.87)	(−75.32)	(5.97)		(1.27)	(−56.17)	(4.16)	
High	5.488***	−0.493***	1.313***	35.16	3.330	−0.519***	11.600***	34.94
	(3.79)	(−64.23)	(5.99)		(1.44)	(−47.61)	(3.13)	
High–Low	1.050	0.059***	0.691***	0.59	11.700***	0.094***	−17.000***	0.69
	(0.61)	(6.50)	(2.66)		(4.31)	(7.25)	(−3.87)	
TLS	11.000***	−0.095***	2.193***	0.71	5.564	−0.095***	23.000***	0.38
	(4.91)	(−3.70)	(6.46)		(1.56)	(−5.64)	(4.00)	

highest (lowest) BM portfolio on day t. As a comparison, we report results of the TLS strategy as well as results of the simple difference (High–Low hereafter) in all tables of this paper. We further define the difference between the return of TLS_{MA} and that of the buy-and-hold strategy as TLS_{MAP}, to demonstrate the usefulness of the proposed TLS strategy, which can be expressed as:

$$TLS_{MAP,t,L} = \begin{cases} 0, & \text{if } P_{10,t-1} > A_{10,t-1,L} \text{ and } P_{1,t-1} < A_{1,t-1,L}; \\ R_{1,t} - R_{f,t}, & \text{if } P_{10,t-1} > A_{10,t-1,L} \text{ and } P_{1,t-1} > A_{1,t-1,L}; \\ R_{f,t} - R_{10,t}, & \text{if } P_{10,t-1} < A_{10,t-1,L} \text{ and } P_{1,t-1} < A_{1,t-1,L}; \\ R_{1,t} - R_{10,t}, & \text{otherwise}. \end{cases} \tag{7}$$

We simultaneously report average returns of TLS_{MA} and TLS_{MAP} in Table 1, but only report those of TLS_{MAP} in the remaining tables to save space.

2.3. Data description

Our sample consists of daily returns and firm characteristics of all common stocks listed on the TWSE from July 1982 to December 2010. The data are retrieved from the Taiwan Economic Journal (TEJ), which is a local data vendor in Taiwan. Following Fama and French (1992), a firm's book-to-market equity for July of year t to June of year $t + 1$ is calculated as the book value of fiscal year $t - 1$, divided by market equity at the end of calendar year $t - 1$. Financial firms and firms with negative book values are excluded from our sample. As in Chui and Wei (1998), we use Central Bank discount rate as the proxy of the risk-free rate. From the beginning of July in year t to the end of June in year $t + 1$, we follow the methodology described in Section 2.1 in constructing the daily index prices, returns and MA indicators for each of the 10 BM-sorted portfolios. The index prices and returns are calculated using adjusted prices on individual stocks that adjust for the effects of dividend payout, stock splits, and share repurchases. In this paper, all prices and returns are calculated based on the local currency (the New Taiwan dollar). We will show in Section 4.1 that our empirical results remain statistically and quantitatively similar, even if a different currency (specifically, the U.S. dollar) is used in converting stock prices.

3. Empirical results

In this section, we first provide basic characteristics of BM decile portfolios, 10-day MA timing portfolios, the corresponding MAPs, as well as returns of the High–Low and the TLS strategies. We then examine whether returns are abnormal conditioning on risk-based models. Finally, we analyze the source of profitability of MA timing portfolios.

3.1. The profitability of the moving average strategies

We first report the summary statistics of returns on the BM decile portfolios, returns on the 10-day MA timing portfolios, and returns on the corresponding MAPs in Table 1. The average daily return of the 10 equally-weighted BM decile portfolios, as reported in Panel A, ranges from 4.500 basis points (decile 4) to 6.144 basis points (decile 1). The simple difference between the highest and lowest BM portfolios with the buy-and-hold strategy, High–Low, is −0.478 basis points (which is equivalent to an annual return of −1.195%) with a t-statistic of −0.21. The insignificant premium of the High–Low strategy is consistent with the literature (Brown et al., 2008; Chen & Zhang, 1998; Chui & Wei, 1998; Ding et al., 2005; Hung et al., 2012). The MA timing portfolios, labeled as MA(10), have higher returns than their corresponding buy-and-hold BM benchmarks, ranging from 12.290 basis points (decile 2) to 15.430 basis points (decile 10). It should be noted that after considering the MA signals, the highest BM portfolio now has the highest return among the ten deciles, but the returns do not increase monotonically with BM deciles. Another notable phenomenon is that MA timing portfolios have substantially smaller standard deviations than their buy-and-hold benchmarks, resulting in higher Sharpe ratios. In addition, while BM decile portfolios display negative skewness (except for the highest BM decile), the MA timing strategy yields smaller skewness in absolute value across the BM deciles.

But, does the MA timing strategy yield significantly positive return difference between high and low BM decile portfolios? While the answer from the simple difference return of the High–Low strategy (1.644 basis points per day with a *t*-statistic of 0.91) is negative, return of the TLS strategy (significant 21.953 basis points per day with a *t*-statistic of 10.22) indicates otherwise. This suggests that sophisticated investors are able to earn higher returns through trading the BM portfolios based on MA signals, only if they do not misuse trading signals of the short position.

We now turn our attention to the results of MAPs, the difference in returns between the MA timing portfolios and the buy-and-hold portfolios. Since the MA timing portfolios have higher returns than the buy-and-hold portfolios across BM deciles, the returns of MAPs are all positive, ranging from 6.603 basis points (decile 6) to 9.782 basis points (decile 10) per day. While the standard deviations are much smaller than those of the corresponding buy-and-hold deciles, they are not much different from those of the MA timing portfolios. However, the skewness of the MAPs across all deciles is positive except for the highest BM decile. In addition, returns of MAPs with the High–Low and the TLS strategies are 2.122 basis points (*t*-statistic $= 1.33$) and 22.431 basis points (*t*-statistic $= 11.16$), which are consistent with the patterns of the MA timing portfolios.

Results of value-weighted BM decile portfolios are given in Panel B of Table 1. Other than the fact that returns of value-weighted MA timing portfolios are slightly smaller than equally-weighted ones, results are largely similar to those obtained with equally-weighted BM decile portfolios. Therefore, value-weighted MAPs yield smaller returns across BM deciles, ranging from 3.146 basis points to 7.935 basis points. Nevertheless, the premium of High–Low strategy is relatively small and insignificant, while that of the TLS strategy is still significantly positive, for both the MA timing portfolio and MAP. Overall, the summary statistics clearly show that the MA timing strategy performs well, and our TLS strategy does provide significant returns even if the value premium with the buy-and-hold strategy is insignificant in Taiwan. However, it is not clear whether the significant premiums can be explained by risk-based models. We address this issue in the next subsection.

3.2. Does the profitability compensate for risk?

In this subsection, we examine whether profitability of MA signals on the BM decile portfolios and the returns of the TLS strategy can be explained by the CAPM or Fama and French's (1993) three-factor model. The regression results of Eqs. (4) and (5) are reported in Table 2. The results of equally- and value-weighted portfolios are presented in Panels A and B, respectively, which share general patterns, and are summarized as follows. First, the CAPM and Fama–French alphas for each of the decile MAPs, equally- or value-weighted, are all higher than those raw returns reported in Table 1. As in Han et al. (forthcoming), the large risk-adjusted abnormal returns are due to the negative market betas of the 10 MAPs. The market betas become slightly more negative in Fama–French regressions than those in the CAPM case. In addition, all loadings on the SMB factor, and almost all loadings on the HML factor are significantly negative. The only two exceptions are positive HML loadings for decile 1 and decile 2. The evidence indicates that the higher abnormal returns are due to less exposure of the MA timing strategy to these factors.

Second, despite the fact that all decile MAPs have higher risk-adjusted returns, differences in returns between the highest and lowest BM (High–Low) deciles are similar in magnitude for all cases. It is also the case for the TLS strategy, suggesting that risk-factor models fail to account for the profitability of the TLS strategy. It should be noted that market betas and coefficients on SMB and HML factors are all significantly negative for the TLS strategy.

Finally, for the model fitting, the Fama–French three-factor model has better explanatory power than the CAPM for both decile MAPs and the TLS strategy, evidenced by higher adjusted R^2s, but with no particular patterns across the deciles. However, the explanatory power of the CAPM and the Fama–French three-factor model for the TLS strategy is very limited, with adjusted R^2s of only -0.01% and 0.19% for the CAPM, and of 10.99% and 17.27% for the Fama–French three-factor model, again confirming our finding that the two models do not explain the premium of the TLS strategy.

3.3. The components of the moving average strategies

Since we have documented the profitability based on MA timing strategies, the next task is to investigate why MA timing strategies outperform buy-and-hold strategies. The return of the MAPs, defined as the return difference between MA timing strategies ($\widetilde{R}_{j,t,L}$) and buy-and-hold strategies ($R_{j,t}$), can be rewritten as follows:

$$MAP_{j,t,L} = \begin{cases} 0, & \text{if } P_{j,t-1} > A_{j,t-1,L}; \\ R_{f,t} - R_{j,t}, & \text{otherwise.} \end{cases} \tag{8}$$

This suggests that the profitability of MA timing strategies over buy-and-hold strategies stems entirely from the underperformance of $R_{j,t}$ when $A_{j,t-1,L}$ falls below previous day's price, $P_{j,t-1}$. In other words, if the MA strategy is able to correctly predict the time to sell the underlying asset, we expect a higher proportion of positive values of $R_{f,t} - R_{j,t}$ to occur when the MA indicator suggests a selling signal.

To examine this, we first divide the time series of MA timing portfolio j into two groups depending on whether a buying signal or a selling signal was issued by the MA rule, i.e. $P_{j,t-1} > A_{j,t-1}$ or $P_{j,t-1} \leq A_{j,t-1}$. We then calculate proportions of portfolio returns greater, and smaller than the risk-free rate on the following day, which are reported in Table 3. We find that, for the ten BM deciles, the proportion of correct prediction implied by buying signals ($P_{j,t-1} > A_{j,t-1}$) is about 57% for equally-weighted portfolios, and is between 53% and 56% for value-weighted portfolios. The proportion of correct prediction implied by selling signals ($P_{j,t-1} \leq A_{j,t-1}$) ranges from 49.99% for the 5th decile value-weighted portfolio to 54.54% for the 10th decile equally-weighted portfolio. We also test whether the proportion of correct prediction is significantly different from 50%, and find that most of them are significant at the 10% level, with exceptions of the 3rd-, 4th-, and 5th-decile value-weighted portfolios under $P_{j,t-1} \leq A_{j,t-1}$. Most relevant to the focus of this paper is that, for the highest- and the lowest-BM decile portfolios which comprise the TLS strategy, the MA signals are able to successfully predict returns in the following day.

4. Robustness

In this section, we examine the robustness of MA timing strategy profitability and the significance of premium produced by the TLS strategy in several dimensions. We first examine whether our results are robust to different currencies used and the U.S. Fama–French three-factor model. We then consider alternative lag lengths for the MA indicator. We also analyze trading behaviors implied by the MA timing strategies, and calculate break-even transaction costs. We further examine whether the profitability is robust in subperiods, and whether the profitability is related to business cycle and market timing.

4.1. The effects of exchange rates and the U.S. Fama–French three-factor model

Since the results in Section 3 are based on prices and returns calculated in the local currency (the New Taiwan dollar), it is of interest to see if our proposed TLS strategy is profitable for foreign investors. In other words, it is important to examine whether our results are robust to exchange rates. In this section, we first convert prices for individual stocks into U.S. dollars, calculate resulting prices and returns for the BM portfolios, and then repeat our methodology described in Section 2. We report average returns of Eqs. (3) and (7), and two sets of risk-adjusted returns based on the Taiwan Fama–French three-factor model and the U.S. Fama–French three-factor model, respectively. We use the U.S. Fama–French three-factor model as a robustness check because the world markets may be integrated, and the U.S. Fama–French model may serve as a better asset-pricing model to explain stock returns.[2] We download the daily returns of the U.S. Fama–French factors from Kenneth R. French's website.[3] Table 4 reports the results.

Average returns of equally- and value-weighted MAPs for TLS strategies are 16.450 basis points and 10.630 basis points, which are slightly lower than the 22.431 basis points of the equally-weighted MAP and the 17.165 basis points of the value-weighted MAP denominated in the New Taiwan dollar as reported in Table 1. Nevertheless, they are still significant at the 1% level, suggesting that the TLS strategy is profitable after a different currency is considered. Moreover, intercepts from the time-series regressions on the Taiwan Fama–French model and the U.S. Fama–French model are quantitatively the same with the average returns. The evidence suggests that our empirical results are robust to the two sets of risk

[2] We thank the anonymous referee for pointing this out to us.
[3] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

adjustments. It should also be noted that the adjusted R^2 for the U.S. Fama–French model is quite low, indicating that the U.S. Fama–French model has little power in explaining the MAP returns for BM decile portfolios and the two zero-cost trading strategies.

4.2. Alternative lag lengths

We consider profitability of MAPs with various lag lengths from shorter to longer intervals, that is, 5-, 20-, 50-, 100-, and 200-day MAs. Panels A to C of Table 5 show average returns, CAPM alphas and Fama–French alphas for MAPs of various lag lengths. These results are similar to those of 10-day MAs, but two interesting features emerge.

First, MA timing strategies still outperform buy-and-hold strategies across BM portfolios regardless of the lag length used to calculate the moving average. Almost all average returns, CAPM alphas and Fama–French alphas are significantly positive for the 10 BM MAPs, with two exceptions that the equally- and value-weighted raw returns of 100- and 200-day MAPs are mostly negative or insignificant. The phenomenon is due to the fact that the magnitude of abnormal returns decreases as the lag length increases. The decline is more apparent for lower BM decile portfolios.

Second, despite the decreasing trend of abnormal returns in the MAPs as the lag length increases, the TLS strategy still generates significantly positive premiums and alphas for all lag lengths. The premium of the TLS strategy also exhibits a decreasing trend as the lag length increases, except for the 5-day MAs. For example, the average return of the 20-day TLS strategy is 21.070 basis points, which is about 94% of the 10-day TLS strategy (22.431 basis points reported in Table 1). In contrast, the 200-day TLS strategy generates an average return of 8.870 basis points, which is about 40% of the 10-day TLS strategy. There is an apparent monotonic relation between the lag length from 10-day to 200-day and the profitability of the TLS strategy. The average return of the 5-day TLS strategy, however, is only about 88% (19.690 basis points) of the 10-day TLS strategy, suggesting that timing strategies with shorter intervals do not yield higher returns than the 10-day lag length.[4] A possible explanation is that the trading information embedded in the 5-day interval may be too noisy, so that investors may buy or sell too early according to the 5-day MA trading signal.

4.3. Holding days, trading frequency and transaction costs

A major difference between the MA timing strategy and the buy-and-hold strategy is that trading underlying assets according to MA signals would usually incur additional transaction costs. Thus, it is important to know how often investors can afford to trade when they follow the MA timing strategy. If trades occur too often, profitability could be eroded by transaction costs. We address this issue by analyzing average holding days, the overall proportion of holding days, and trading frequencies of MA timing portfolios. We further analyze returns of MAPs after excluding transaction costs.

Average holding days (Holding), as reported in Table 6, increase monotonically with the lag length. The 5-day MA timing strategy has an average of about 4 to 5 holding days for both equally- and value-weighted portfolios, while the 200-day MA timing strategy has an average holding days ranging from 33 to 66 days for equally-weighted portfolios, and from 40 to 56 days for value-weighted portfolios. This is not surprising as longer lag lengths capture longer trends, resulting in longer holding days. Furthermore, there exists no particular trend in holding days across BM deciles, and the average holding days are quite similar across BM deciles for lag lengths less than 20 days.

These results imply that trading frequency is inversely related to the lag length, which is confirmed in Table 6. The fraction of trading days (Freq), i.e., the proportion of the number of days that trades occur to the total number of days in our sample, is about 10% to 11% for 5-day lag length, and is about 0.9% to 1.6% for 200-day lag length. The proportion is monotonically decreasing as lag length increases.

[4] This is consistent with Han et al. (forthcoming), who claim in their footnote 11 that 3- and 5-day MA timing strategies do not generate higher performance than the 10-day MA timing strategy.

This suggests that investors have to trade more often if they follow shorter MAs than longer MAs, leading to higher transaction costs.

A further question is whether MA timing strategies are still profitable after accounting for transaction costs. To examine this issue, we follow Balduzzi and Lynch (1999), Lynch and Balduzzi (2000), Han (2006), and Han et al. (forthcoming) by assuming that we incur transaction costs for trading decile portfolios but no costs for trading the risk-free asset. That is, returns on the MA timing strategy for portfolio j in the presence of transaction cost τ per trade now become:

$$\widetilde{R}_{j,t,L} = \begin{cases} R_{j,t}, & \text{if } P_{j,t-1} > A_{j,t-1,L} \text{ and } P_{j,t-2} > A_{j,t-2,L}; \\ R_{j,t} - \tau_1, & \text{if } P_{j,t-1} > A_{j,t-1,L} \text{ and } P_{j,t-2} < A_{j,t-2,L}; \\ R_{f,t}, & \text{if } P_{j,t-1} < A_{j,t-1,L} \text{ and } P_{j,t-2} < A_{j,t-2,L}; \\ R_{f,t} - \tau_2, & \text{otherwise}. \end{cases} \quad (9)$$

where τ_1 (τ_2) is the transaction cost when investors buy (sell) securities. Trading securities in Taiwan stock market typically involve a maximum commission fee of 14.25 basis points when investors either buy or sell stocks, and a transaction tax of 30 basis points applicable only when investors sell stocks. For short-selling securities on the TWSE, there is an additional security borrowing fee, which are mostly lower than 1.00% daily.[5] Therefore, we set the daily security borrowing fee rate at 100 basis points. These direct fees amount to a maximum of 158.5 basis points in total for a round-trip transaction on the short position, and only 58.5 basis points for the long position. In addition to these explicit fees, transaction costs should also contain indirect costs such as price impact, which are often difficult to measure. Hence, to properly examine the effect of transaction costs on our results, we follow Han et al. (forthcoming) in considering break-even transaction costs that make the average return of the MAPs zero.

Break-even transaction costs (BETCs) for a round trip (i.e., $\tau_1 + \tau_2$) in basis points for each of the BM decile portfolio, the High–Low strategy and the TLS strategy with different lag lengths are reported in Table 6. BETCs for those portfolios with negative MAP returns are reported as n.a., because negative cost is not applicable. It should be noted that since the TLS and High–Low strategies contain long and short positions, their BETCs are calculated on the basis of a round-trip transaction on both positions. Generally, we do not observe particular patterns of BETC across BM deciles or lag lengths. However, we document two interesting phenomena for High–Low and TLS strategies. First, given that the fraction of trading days (Freq) is the same for the two strategies, which is equal to the sum of the fractions of decile 1 and decile 10, the TLS strategy has higher BETC than the High–Low strategy for all lag lengths. Among which, the High–Low strategy even produces a negative BETC under the 5-day MA signal. Second, the BETC for the TLS strategy is considerably high, which ranges from 57.23 basis points (value-weighted MAP(5) strategy) to 413.11 basis points (equally-weighted MAP(100) strategy). Compared with the explicit fees mentioned above, a TLS strategy that results in a BETC higher than 217 basis points (including 58.5 basis points for the long position and a maximum of 158.5 basis points for the short position) demonstrates its ability to earn economically significant abnormal returns after the highest explicit transaction costs are accounted for.[6] That is, for the MAPs with lag lengths greater than 20 days, we are still confident with the trading strategy's profitability. Moreover, if investors are able to borrow securities at the minimum fees, the MAP(10) strategy is also profitable since the BETC for the equally- (value-)weighted strategy is 161.82 (119.60) basis points, which is higher than the minimum transaction costs of 118 basis points (including 58.5 basis points for the long position, 58.5 basis points for the short position and 1 basis point of borrowing fee).

[5] According to the regulation of Security Borrowing and Lending on the TWSE, the maximum daily security borrowing fee rate is set at 7% of the daily closing price, while the actual fee rate is set by investors. And, as Hsu (2009) points out, actual daily security borrowing fee rate on the TWSE ranges between 0.01% to 7.00%, and most of them are lower than 1.00%.

[6] We appreciate the anonymous referee for bringing up this issue.

4.4. Subperiod analysis

We further examine whether our results are robust in subsamples. To do so, we divide the entire sample into two subperiods with roughly equal length, and report Fama–French alphas of 10-day MAPs and the two strategies in Table 7. In both subperiods, the ten BM MAPs all yield significantly positive alphas, similar to the case of the entire sample period. Abnormal returns of TLS strategies are all significantly positive in subperiods, consistent with those results reported in Table 2. In addition, alphas are quantitatively the same in both subperiods for equally-weighted portfolios, but are slightly higher in the first subperiod than in the second subperiod for value-weighted portfolios. Overall, the results continue to provide supportive evidence for the profitability of the TLS strategy.

4.5. Are moving average signals related to business cycles?

In addition to the subperiod analyses, we further investigate whether there exist some patterns between predictability of MA signals and business cycles. We follow Liew and Vassalou (2000) and Cooper, Gutierrez, and Hameed (2004) in identifying business cycles in two ways. First, we follow Liew and Vassalou (2000) in defining good and bad states according to the GDP growth, and perform the following regressions:

$$\begin{aligned} MAP_{j,t,L} &= \alpha_{j,L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,SMB}R_{SMB,t} + \beta_{j,L,HML}R_{HML,t} + \beta_{j,L,Good}D^{GDP}_{Good,t} \\ &\quad + \beta_{j,L,Bad}D^{GDP}_{Bad,t} + \varepsilon_{j,L,t}, \\ TLS_{t,L} &= \alpha_L + \beta_{L,MKT}R_{MKT,t} + \beta_{L,SMB}R_{SMB,t} + \beta_{L,HML}R_{HML,t} + \beta_{L,Good}D^{GDP}_{Good,t} \\ &\quad + \beta_{L,Bad}D^{GDP}_{Bad,t} + \varepsilon_{L,t}, \end{aligned} \tag{10}$$

where $D^{GDP}_{Good,t}$ is a dummy variable indicating a good state of the economy when the GDP growth rate in that quarter is of the highest 25% for the whole sample period, and $D^{GDP}_{Bad,t}$ is a dummy variable indicating a bad state of the economy when the GDP growth rate in that quarter is of the lowest 25% for the whole sample period. If coefficients on $D^{GDP}_{Good,t}$ or $D^{GDP}_{Bad,t}$ are significantly positive, one may conclude that the predictability is particularly stronger in expansionary or recessionary periods.

We next follow Cooper et al. (2004) in identifying good and bad states based on market returns, and perform the following regressions:

$$\begin{aligned} MAP_{j,t,L} &= \alpha_{j,L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,SMB}R_{SMB,t} + \beta_{j,L,HML}R_{HML,t} + \beta_{j,L,Bad}D^{Market}_{Bad,t} + \varepsilon_{j,L,t}, \\ TLS_{t,L} &= \alpha_L + \beta_{L,MKT}R_{MKT,t} + \beta_{L,SMB}R_{SMB,t} + \beta_{L,HML}R_{HML,t} + \beta_{L,Bad}D^{Market}_{Bad,t} + \varepsilon_{L,t}, \end{aligned} \tag{11}$$

where $D^{Market}_{Bad,t}$ is a dummy variable indicating a bad state of the market if the market's past three-year return prior to the beginning of the strategy's holding period is negative. If coefficients on $D^{Market}_{Bad,t}$ are significantly negative, one may conclude that the predictability is particularly weaker in bad market states.

We show in Table 8 that our results are not driven by business cycles. For the model in Eq. (10), coefficients on $D^{GDP}_{Good,t}$ and $D^{GDP}_{Bad,t}$ are mostly insignificant for 10-day MAPs across BM deciles as well as High–Low and TLS strategies. In addition, alphas still retain their significance when the two dummy variables are included in the regressions. For the model in Eq. (11), coefficients on $D^{Market}_{Bad,t}$ are negative and insignificant in most cases. Intercepts for the TLS strategy even larger than those in Eq. (10). Hence, we conclude that our results are not affected by business cycles, regardless of the definitions of market states.

4.6. The market timing of moving average strategies

To further understand why MA timing and TLS strategies exhibit superior performance than the buy-and-hold strategy, we examine whether there is any market-timing ability of MA timing and TLS strategies. By employing two popular approaches proposed by Treynor and Mazuy (1966) and Henriksson and Merton (1981), Han et al. (forthcoming) indicate successful market timing by the MA timing strategy formed on volatility portfolios, but market timing alone does not explain abnormal returns of MAPs. The first approach is the quadratic regression of Treynor and Mazuy (1966):

$$\begin{aligned} MAP_{j,t,L} &= \alpha_{j,L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,MKT^2}R^2_{MKT,t} + \varepsilon_{j,t,L}, \quad j = 1, \ldots, 10, \\ TLS_{t,L} &= \alpha_L + \beta_{L,MKT}R_{MKT,t} + \beta_{L,MKT^2}R^2_{MKT,t} + \varepsilon_{t,L}, \end{aligned} \tag{12}$$

where $R^2_{MKT,t}$ is the squared market excess return, and the significantly positive coefficients of β_{j,L,MKT^2} and β_{L,MKT^2} indicate successful market-timing ability. The second approach is the regression of Henriksson and Merton (1981), which takes the following form:

$$\begin{aligned} MAP_{j,t,L} &= \alpha_{j,L} + \beta_{j,L,MKT}R_{MKT,t} + \gamma_{j,L,MKT}R_{MKT,t}I_{r_{MKT,t>0}} + \varepsilon_{j,t,L}, \quad j = 1, \ldots, 10, \\ TLS_{t,L} &= \alpha_L + \beta_{L,MKT}R_{MKT,t} + \gamma_{L,MKT}R_{MKT,t}I_{r_{MKT,t>0}} + \varepsilon_{t,L}, \end{aligned} \tag{13}$$

where $I_{r_{MKT,t>0}}$ is an indicator function taking the value of one when the market excess return is greater than zero, and zero otherwise. The significantly positive coefficients of $\gamma_{j,L,MKT}$ and $\gamma_{L,MKT}$ indicate successful market-timing ability.

We follow Han et al. (forthcoming) in examining the market-timing issue by applying these two approaches, and report regression results for the 10-day MAPs in Table 9.[7] Two interesting results are revealed in Table 9. First, all coefficients on β_{MKT^2} and γ_{MKT} are significantly positive, with one exception that the High–Low strategy has a significantly negative γ_{MKT}. This suggests successful market timing by MAPs across BM deciles and the TLS strategy, regardless of the model specifications used to capture the market-timing ability.

Second, after considering the market-timing effect, alphas of the 10 MAPs are still significantly positive under Treynor–Mazuy regressions, but 7 out of them become negative under Henriksson–Merton regressions. Significantly negative alphas mainly occur in lower BM deciles. Moreover, the TLS strategy still has significant and positive alphas, except for the case of value-weighted TLS strategy under Henriksson–Merton regression, which is 5.564 basis points with a *t*-statistic of 1.56. Despite this, it still yields an annual return of 13.91% per year, which should be economically significant. Overall, consistent with Han et al. (forthcoming), our results show supportive evidence of the market-timing ability, but market timing alone does not explain the profitability of the TLS strategy.

5. Conclusion

There is ample evidence suggesting that the BM effect does not exist in Taiwan stock market. A common feature among the vast literature is the adoption of a buy-and-hold strategy with annual rebalancing, which is proposed by Fama and French (1992). In this paper, we examine the role of technical analysis on the value investing, and whether MAs signals provide additional information in predicting the return difference between high- and low-BM portfolios. We follow Han et al. (forthcoming) in constructing the MA timing strategy across BM portfolios, and document superior performance for the MA timing strategy over the buy-and-hold strategy.

We further contribute to the finance literature by proposing a long–short portfolio with zero cost conditioning on MA signals. The new strategy suggests a buying signal when the index price of the highest BM portfolio is higher than its MA indicator, and a short-selling signal when the index price of the lowest BM portfolio is lower than its MA indicator. Under such a construct, we show that the new strategy yields significantly positive return, and provides higher returns than the standard buy-and-hold strategy in Taiwan. The abnormal return is both economically and statistically significant, and cannot be explained by either the CAPM or Fama and French's (1993) three-factor model.

[7] As a robustness test, we also examine the market-timing ability of the HML factor using the approaches of Treynor and Mazuy (1966) and Henriksson and Merton (1981), and find that the market-timing ability of the HML factor is weaker than the market portfolio. To save space, we do not report those results, which are available upon request. We thank the anonymous referee for bringing up this issue.

The significance of the premium under the newly proposed zero-cost strategy is quite robust in several aspects. First, the overall results are robust to exchange rates. Second, the premium is significant regardless of lag lengths of MA signals. Third, it turns out that investors adopting MA signals do not have to trade BM portfolios too often, and that the break-even transaction costs are reasonably large to ensure profitability of such strategies. Fourth, the results sustain in subsamples and are not driven by business cycles. Finally, we document successful market-timing ability of the new strategy, but market timing alone does not explain abnormal returns.

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