

# Moving Average Timing Strategy from a Volatility Perspective: Evidence of the Taiwan Stock Market

Shyh-Weir Tzang<sup>(✉)</sup>, Yung-Shun Tsai, Chun-Ping Chang, and Ya-Ping Yang

Department of Finance, Asia University, 500, Liu-Feng Road,  
Wu-Feng District, Taichung, Taiwan  
swtzang@gmail.com, gicha.tsai@gmail.com, l2space@hotmail.com,  
pinpin0217@yahoo.com.tw

**Abstract.** We apply the approach of [5] by examining whether the portfolios based on the trend-following strategy delivers abnormal returns. Sorted by volatility in previous year, portfolios are traded by following moving average timing strategy to examine their investment performance within the sample period from 1996–2011 for companies listed in the Taiwan stock market. We find that the moving average timing strategy outperforms the buy-and-hold strategy. The CAPM and the Fama-French three-factor models can explain the abnormal returns of the moving average timing strategy. Furthermore, the performance 10-day moving average timing strategy outperforms other timing strategies based on 20-, 50-, 100- and 200-day moving average across volatility quintiles. That means higher volatility quintile portfolios with 10-day moving average timing strategy tend to have better performance than those portfolios with longer days of moving average timing strategy.

**Keywords:** Moving average · Trend following · Volatility · Market timing

## 1 Introduction

The economy of the U.S.A. went through the dotcom bubble during the late of 1990s which made the Fed to lower interest rate to boost its economy. However, the subprime financial crisis in American real estate market in late 2008 dragged the world economy into another recession in history. In the following years, an easing monetary policy seemed to become only way to rejuvenate the economy of countries in the world. The investment risk in stock market had also risen to a record high during that period and therefore the volatility of returns becomes a commonly-used measure of investment risk. For example, the VIX index, an average volatility of stock market implied by the traded options, is a popular risk measure to represent the degree of fear implied by investors.

The relationship between return and risk has been widely documented in literature. [4, 11] show a positive relationship between stock returns and volatilities. [10] also find a positive relationship between volatilities and UK stock returns from 1965–1989. [12] find a positive relationship for Latin America but not so obvious in Asian countries. However, [8] provide evidence for a negative relationship between volatility and stock returns based on 12 international stock market from 1980–2001. [7] posit that the negative relationship between return and volatilities is caused by trader's behavior and the extreme changes in index returns.

In the market, technical analysis has been widely used by practitioners and traders. Moving average (MA), or so-called the trend-following strategy, is one of the most popular technical tools in the market trading and has drawn substantial attention from academics. [1, 9] provide support for the profitability of MA strategy in the trading. [2] delivers an in-depth perspective on the trend-following strategy. [3] even conduct a simple MA strategy using 200-day MA based on the sample of S&P500 and generate portfolios with equity-like returns and bond-like risk. [15] theoretically proves that the MA strategy based on certain fixed rule of asset allocation outperforms other investment strategies. Under circumstances with great uncertainty as in the real market, they also prove that the generalized MA strategy outperforms other dynamic portfolios. [14] further show that MA has better performance in the emerging stock markets like Malaysia, Thailand, Indonesia, and the Philippines than in other more developed market.

This study aims to explore whether the market-timing MA strategy outperforms buy-and-hold strategy in the Taiwan stock market. Besides, we also try to verify whether high volatility portfolios deliver better performance in risk-return metrics. Fama-French 3 factor models are also used to explain the returns of market-timing MA strategy.

## 2 Data and Model

The daily closing prices for stocks are obtained from Taiwan Economic Journal (TEJ) database from 1996/1/4 to 2011/12/31. The number of observations in each year is listed in Table 1. The prices of financial institutions, depository receipts and stocks over the counter are not included in our data sample. TEJ also provides the Fama-French 3 factor returns, i.e., market premium, size and value, on daily frequency.

We follow the approach of [5] to define the portfolios based on volatility. First of all, we calculate each stock's annual volatility by using its daily return and construct decile portfolios ranked by volatility from smallest to largest at the end of each sampled year. Based on the closing prices for stocks in each decile, we construct each portfolio ( $j$ ) at the beginning of next year and calculate its

portfolio price index ( $P_{jt}$ ) and portfolio return ( $R_{jt}$ ) on each date  $t$ . The portfolio price index is calculated as follows:

$$P_{jt} = \sum_{i=1}^{n_j} w_i P_{ijt}, j = 1, \dots, 10, \tag{1}$$

where  $n_j$  is the number of stocks in  $j$ -th decile.  $w_i$  is the market capitalization for stocks at the end of previous year. We further calculate  $L$ -day moving average of  $P_{jt}$  to be defined as  $MP_{jt,L}$ :

$$MP_{jt,L} = \frac{P_{jt-L-1} + P_{jt-L-2} + \dots + P_{jt}}{L}, \tag{2}$$

where  $L = 10, 20, 50, 100$  and  $200$  days.

Then we construct market-timing MA strategy as follows. If  $P_{jt} > MP_{jt,L}$ , then we will long the position of  $P_{jt}$  and convert it into cash to earn risk free rate if  $P_{jt} \leq MP_{jt,L}$ . The return of this market-timing MA strategy is defined as  $RMP_{jt,L}$ . We also construct buy-and-hold portfolio for comparison purpose and its return are defined as  $RBH_{jt}$ . The excess return of  $RMP_{jt,L}$  is defined as  $\widetilde{RMP}_{jt,L}$  where:

$$\widetilde{RMP}_{jt,L} = RMP_{jt,L} - RBH_{jt} \tag{3}$$

**Table 1.** Number of firm observations (1996–2011)

Year	Obs	Year	Obs	Year	Obs	Year	Obs	Year	Obs
1996	240	1997	276	1998	308	1999	353	2000	415
2001	470	2002	515	2003	575	2004	612	2005	629
2006	643	2007	656	2008	674	2009	686	2010	713
2011	748								

### 3 Empirical Results

#### 3.1 Summary Statistics

Table 2 shows the mean, standard deviation, skewness and Sharpe ratio for  $RBH$ ,  $RMP$  and  $\widetilde{RMP}$ . Due to the limited pages of the paper, we only present the results of 10-day MA strategy for illustrative purpose. As the standard deviation increases from decile 1 to 10, the mean returns for  $RMP$  and  $\widetilde{RMP}$  increases monotonically (except in volatility-decile 5 and 6 for  $RMP$ , and volatility-decile 5 for  $\widetilde{RMP}$ ). The range of  $RMP$  and  $\widetilde{RMP}$  lie in (0.1907, 0.3062) and (0.1405, 0.2714), respectively. However,  $RBH$  does not show any positive

relationship between volatility and mean return. Besides, both  $RMP$  and  $\widetilde{RMP}$  show a positive skewness but  $RBH$  shows a negative skewness. The annualized Sharpe ratios of  $RMP$  are also found to be consistently higher than those of  $RBH$ .

**Table 2.** Summary statistics for  $RBH$ ,  $RMP$  and  $\widetilde{RMP}^a$

Decile	Mean	Std	Skewness	Sharpe ratio	Mean	Std	Skewness	Sharpe ratio	Mean	Std	Skewness
	$RBH$				$RMP$				$\widetilde{RMP}$		
1	0.0524	1.0554	-0.3722	0.9418	0.1907	0.6825	1.4579	5.3013	0.1405	0.7705	1.5167
2	0.0436	1.2786	-0.3165	0.6474	0.2043	0.7894	1.4411	4.9115	0.1633	0.9729	1.1303
3	0.0453	1.3798	-0.3537	0.6227	0.2176	0.8682	1.3398	4.7562	0.1789	1.0324	1.3095
4	0.0352	1.4547	-0.3375	0.4595	0.2432	0.8704	1.4192	5.3023	0.2161	1.1139	1.0852
5	0.0345	1.5519	-0.3149	0.4223	0.2360	0.9762	1.1451	4.5877	0.2091	1.1592	1.1839
6	0.0263	1.6147	-0.3443	0.3087	0.2280	0.9641	1.0205	4.4865	0.2131	1.2504	0.9487
7	0.0319	1.6796	-0.3447	0.3598	0.2579	0.9975	0.9882	4.9047	0.2390	1.2973	0.9147
8	0.0283	1.7465	-0.3337	0.3071	0.2749	1.0101	1.1384	5.1639	0.2566	1.3662	0.8533
9	0.0413	1.8012	-0.3098	0.4354	0.2835	1.0989	0.9828	4.8954	0.2581	1.3622	0.9711
10	0.0558	1.8884	-0.2654	0.5602	0.3062	1.1489	1.0640	5.0563	0.2714	1.4280	0.9199

<sup>a</sup>Portfolios are ranked into 10 groups at the end of each year by their volatilities in previous year. Decile 1 is the portfolio with the smallest volatility.  $RBH$  is the return on buy-and-hold portfolio;  $RMP$  is the return on market-timing MA strategy;  $\widetilde{RMP}$  is excess return on market-timing MA strategy. Due to the limited pages of the paper, here we only present the results of 10-day MA strategy for illustrative purpose. std is standard deviation.

### 3.2 Fama-French 3 Factor Model

We further use Fama-French 3 factor model to test the risk exposure of  $\widetilde{RMP}$  to market premium ( $MKT$ )<sup>1</sup>, size ( $SMB$ ) and value factors ( $HML$ ). For illustrative purpose, we still use 10-day MA strategy to see if it can deliver significant alpha value.

$$\widetilde{RMP}_{jt,10} = \alpha_j + \beta_{j,1}MKT_t + \beta_{j,2}SMB_t + \beta_{j,3}HML_t + \varepsilon_{jt} \quad (4)$$

By Table 3, we find that all of the estimated parameters ( $\alpha, \beta_{mkt}, \beta_{smb}, \beta_{hml}$ ) are significantly different from zero. The estimated  $\alpha$  values are also found to increase monotonically from the lowest-volatility decile to highest volatility decile (except a slight drop in the fifth decile but increasing afterwards), a result consistent with [5]. The highest-volatility decile also delivers an alpha that is almost twice as large as that of the lowest-volatility decile (0.2772/0.1428). The market betas also exhibit a decreasing trend across volatility deciles (from -0.3798 to -0.7469).

<sup>1</sup>  $MKT$  is the difference between daily index return of the Taiwan stock market and risk-free rate which is proxied by 1-year time deposit rate.

**Table 3.** Fama-French 3 factor of 10-day  $\widetilde{RMP}$  strategy<sup>a</sup>

Decile	$\alpha$	$\beta_{mkt}$	$\beta_{smb}$	$\beta_{hml}$	adj- $R^2$
1	0.1428*** (-15.4495)	-0.3798*** (-23.1330)	-0.2474*** (-11.5243)	-0.1362*** (-11.4636)	0.5115
2	0.1654*** ( 14.9936)	-0.4991*** (-24.4011)	-0.3746*** (-15.3486)	-0.2024*** (-14.0591)	0.5646
3	0.1809*** (13.8377)	-0.5212*** (-23.3903)	-0.3943*** (-15.0076)	-0.2229*** (-12.8830)	0.5536
4	0.2189*** (19.2143)	-0.5934*** (-70.3102)	-0.4677*** (-25.6748)	-0.1963*** (-18.0895)	0.5851
5	0.2120*** (17.5398)	-0.6013*** (-67.1546)	-0.4397*** (-22.7474)	-0.2264*** (-19.6620)	0.5687
6	0.2168*** (17.1331)	-0.6730*** (-71.7915)	-0.4903*** (-24.2305)	-0.2111*** (-17.5125)	0.5938
7	0.2435*** (18.8304)	-0.7108*** (-74.1744)	-0.4914*** (-23.7583)	-0.1922*** (-15.5955)	0.6056
8	0.2612*** (19.4497)	-0.7644*** (-76.8163)	-0.5869*** (-27.3260)	-0.1714*** (-13.3940)	0.6166
9	0.2632*** (18.6322)	-0.7396*** (-70.6663)	-0.5436*** (-24.0612)	-0.1341*** (-9.9616)	0.5734
10	0.2772*** (17.8749)	-0.7469*** (-65.0133)	-0.5118*** (-20.6391)	-0.1229*** (-8.31942)	0.5322

<sup>a</sup>  $\widetilde{RMP}$  is the return difference between  $RMP$  and  $RBH$ . The regression is run by Eq. (4).

<sup>b</sup>\*\*\* denotes 1% significance level. Number in parenthesis denotes the Newey-West adjusted robust  $t$ -statistics.

### 3.3 10-, 20-, 50-, 100- and 200-day MA strategy

We further provide empirical evidence to verify the performance of MA strategy when  $L = 20, 50, 100$  and  $200$  days. By Table 7, the mean return of 10- and 20-day MA strategy increases monotonically with the volatility decile both of which consistently outperform all other MA strategies. However, 10-day MA strategy has the best performance among all other days of MA strategy. 200-day MA strategy has the worst performance base on its insignificant mean and alpha returns.

### 3.4 Holding Days and Trading Frequency

The average holding days (HD) is the ratio of total holding days to the number of trades. The trading frequency is the number of trades divided by 250 trading days per year. By Table 4, we find that the average trading days increase with the days of MA strategy, a result consistent with intuition. For example, a 10-day MA strategy in volatility-decile 1 has an average trading days of 6.77 and it

increases to 193 days for 200-day MA strategy in the same volatility decile. The trading frequency of 10-day MA strategy in volatility-decile 1 is 17.28% vs. 0.48% for 200-day MA strategy which correspond to the number of trades of 43.2 vs. 1.2 within an year, or an equivalent of average 5.79 and 208 days between each trade.

**Table 4.** Average holding days (HD) and trading frequency (TF) for 10-, 20-, 50-, 100- and 200-day MA strategies<sup>a</sup>

Decile	10 days		20 days		50 days		100 days		200 days	
	HD	TF	HD	TF	HD	TF	HD	TF	HD	TF
1	6.77	0.1728	10.59	0.1195	27.13	0.0525	50.32	0.0295	193.00	0.0048
2	6.03	0.1815	10.02	0.1160	20.68	0.0615	58.79	0.0238	196.44	0.0045
3	6.75	0.1693	11.05	0.1095	27.71	0.0503	62.86	0.0260	130.57	0.0070
4	6.45	0.1703	10.29	0.1110	23.15	0.0540	81.94	0.0190	132.81	0.0065
5	7.19	0.1583	11.40	0.1028	27.75	0.0503	78.51	0.0218	118.13	0.0075
6	7.00	0.1575	11.60	0.0995	23.96	0.0548	86.18	0.0205	111.81	0.0078
7	6.80	0.1638	12.56	0.0915	29.80	0.0443	64.30	0.0248	144.83	0.0060
8	6.67	0.1603	10.29	0.1073	23.67	0.0515	58.20	0.0250	116.80	0.0075
9	6.57	0.1648	10.46	0.1088	23.26	0.0540	47.33	0.0308	124.75	0.0070
10	6.44	0.1668	10.71	0.1053	19.58	0.0284	62.49	0.0105	106.12	0.0083

<sup>a</sup>Average holding days (HD) is the ratio of total holding days to the number of trades. Trading frequency (TF) is the number of trades divided by 250 trading days per annum.

### 3.5 Market timing test

To identify the what sources contribute to the superior returns of  $\widetilde{RMP}$  of 10-day MA strategy, we follow [6, 13] to estimate following regressions:

$$\widetilde{RMP}_{jt,L} = \alpha_j + \beta_{j,mkt}^1 MKT_t + \beta_{j,mkt}^2 MKT_t^2 + \varepsilon_{j,t}, \tag{5}$$

where the significantly positive  $\beta_{j,mkt}^2$  indicates successful market timing.

$$\widetilde{RMP}_{jt,L} = \alpha_j + \beta_{j,mkt}^1 MKT_t + \gamma_{j,mkt} MKT_t I_{mkt>0} + \varepsilon_{j,t}, \tag{6}$$

where  $I_{mkt>0}$  is indicator function when market premium ( $MKT_t$ ) is positive. A significantly positive  $\gamma_{j,mkt}$  indicates successful market timing.

Tables 5 and 6 report the estimated coefficients of Eqs. (5) and (6). Both tables show significantly positive coefficients for  $\beta^2$  and  $\gamma$ . However,  $\alpha$ s in Table 5 are all significantly positive and they are increasing in higher-volatility decile.

**Table 5.**  $\widetilde{RMP}_{jt,L} = \alpha_j + \beta_{j,mkt}^1 MKT_t + \beta_{j,mkt}^2 MKT_t^2 + \varepsilon_{j,t}$

Decile	$\alpha$	$\beta_{mkt}^1$	$\beta_{mkt}^2$	adj- $R^2$
1	0.0293***(2.9862)	-0.3108***(-25.8178)	0.0490***(14.0441)	0.4894
2	0.0409***(2.9051)	-0.3970***(-23.7876)	0.0544***(10.1220)	0.4766
3	0.0318**(2.2404)	-0.4124***(-24.9255)	0.0649***(11.3151)	0.4792
4	0.0836***(5.2361)	-0.4695***(-25.0197)	0.0591***(9.7024)	0.4961
5	0.0524***(3.6036)	-0.4814***(-26.1951)	0.0694***(12.7235)	0.5019
6	0.0622***(3.8899)	-0.5423***(-29.6408)	0.0674***(10.8516)	0.5233
7	0.0990***(6.1948)	-0.5812***(-29.2758)	0.0631***(10.2901)	0.5408
8	0.1188***(6.6854)	-0.6136***(-29.4349)	0.0624***(9.0413)	0.5364
9	0.1227***(6.5591)	-0.6007***(-26.3572)	0.0613***(8.22666)	0.5174
10	0.1247***(6.0664)	-0.6153***(-28.2706)	0.0662***(10.3338)	0.4992

<sup>a</sup>  $\widetilde{RMP}$  is the 10-day MA return difference between  $RMP$  and  $RBH$ . The regression is Eq. (5).

<sup>b</sup>\*\*\*, \*\* and \* denote 1%, 5% and 10% significance level. Number in parenthesis denotes the Newey-West adjusted robust  $t$ -statistics.

**Table 6.**  $\widetilde{RMP}_{jt,L} = \alpha_j + \beta_{j,mkt}^1 MKT_t + \gamma_{j,mkt} MKT_t I_{mkt>0} + \varepsilon_{j,t}$

Decile	$\alpha$	$\beta_{mkt}$	$\gamma$	adj- $R^2$
1	-0.0800***(-5.8546)	-0.5144***(-26.4494)	0.4051***(14.7421)	0.4792
2	-0.0953***(-5.8859)	-0.6359***(-50.59618)	0.4761***(22.6684)	0.4761
3	-0.1296***(-7.1933)	-0.6963***(-27.2469)	0.5658***(15.0208)	0.4781
4	-0.0751***(-3.8274)	-0.7385***(-30.6993)	0.5367***(14.1098)	0.5002
5	-0.1234***(-6.7779)	-0.7880***(-29.7612)	0.6111***(16.1947)	0.5023
6	-0.1034***(-4.7952)	-0.8355***(-33.4965)	0.5843***(13.3322)	0.5217
7	-0.0750***(-3.6902)	-0.8722***(-37.4450)	0.5810***(13.9918)	0.5459
8	-0.0629***(-2.9616)	-0.9100***(-55.2609)	0.5918***(21.5074)	0.5440
9	-0.0594**(-2.5207)	-0.8949***(-30.0409)	0.5879***(12.4933)	0.5259
10	-0.0715***(-2.9905)	-0.9326***(-34.2735)	0.6339***(15.0762)	0.5081

Table 6 show that  $\alpha$ s are significantly negative but remain quite stable ranging from -5.9% to -7.5% in higher-volatility deciles 7 through 10, suggesting that [6] better explains the data than does [13]. However, as both models delivers significant  $\alpha$ s, they are not fully capable of explaining the abnormal returns of 10-day MA strategy.

**Table 7.** Mean return and alphas of  $\widetilde{RMP}$  for 10-, 20-, 50-, 100- and 200-day MA strategy

Decile	10 days		20 days		50 days		100 days		200 days	
	mean	$\alpha$	mean	$\alpha$	mean	$\alpha$	mean	$\alpha$	mean	$\alpha$
1	0.1405*** (11.4915)	0.1428*** (15.4498)	0.1078*** (8.2726)	0.1090*** (12.6323)	0.0803*** (5.7435)	0.0739*** (7.6660)	0.0677*** (4.1631)	0.0536*** (4.8350)	0.0324 (1.1464)	0.0389** (1.9854)
2	0.1633*** (10.5759)	0.1654*** (14.9936)	0.1228*** (7.5423)	0.1233*** (11.2703)	0.1002*** (5.5861)	0.0893*** (7.4241)	0.0879*** (4.0287)	0.0623*** (4.41268)	0.0786** (2.1145)	0.0835*** (3.7270)
3	0.1789*** (10.9168)	0.1809*** (13.8377)	0.1394*** (8.1169)	0.1397*** (6.43951)	0.0992*** (11.4649)	0.0887*** (5.4675)	0.0887*** (4.2008)	0.0652*** (4.3632)	0.0673** (1.9639)	0.0725*** (2.8050)
4	0.2161*** (12.2234)	0.2189*** (19.2143)	0.1634*** (8.7077)	0.1645*** (13.7161)	0.1286*** (6.2222)	0.1160*** (8.6885)	0.0974*** (3.8729)	0.0660*** (4.2623)	0.0727* (1.6888)	0.0786*** (3.0641)
5	0.2091*** (11.3645)	0.2120*** (17.5398)	0.1535*** (7.9104)	0.1549*** (12.0345)	0.1100*** (5.2616)	0.0991*** (6.9852)	0.0935*** (3.8583)	0.0687*** (4.1901)	0.0454 (1.0486)	0.0517* (1.7877)
6	0.2131*** (10.7352)	0.2168*** (17.1331)	0.1641*** (8.0078)	0.1661*** (12.7369)	0.1250*** (5.6436)	0.1143*** (7.7400)	0.1120*** (4.7354)	0.0945*** (5.5961)	0.0735 (1.6028)	0.0804*** (3.1259)
7	0.2390*** (11.6060)	0.2435*** (18.8304)	0.1746*** (8.0430)	0.1775*** (12.4048)	0.1219*** (5.3388)	0.1115*** (6.9070)	0.0976*** (3.5835)	0.0708*** (3.8735)	0.060 (1.2126)	0.0661** (2.5667)
8	0.2566*** (11.8322)	0.2612*** (19.4497)	0.1851*** (8.0990)	0.1882*** (12.9841)	0.1309*** (5.2786)	0.1170*** (7.2624)	0.1158*** (3.9638)	0.0819*** (4.4531)	0.0773 (1.5608)	0.0823*** (2.9558)
9	0.2581*** (11.9356)	0.2632*** (18.6322)	0.1983*** (8.8013)	0.2017*** (12.8181)	0.1301*** (5.3752)	0.1189*** (6.5832)	0.1198*** (4.1526)	0.0903*** (4.4441)	0.0533 (1.0906)	0.0570* (1.7081)
10	0.2714*** (11.9743)	0.2772*** (17.8749)	0.1868*** (7.8091)	0.1912*** (10.2659)	0.1371*** (5.1544)	0.1261*** (5.9456)	0.0925*** (2.9625)	0.0636*** (2.7582)	0.0256 (0.5075)	0.0307 (0.7713)

## 4 Conclusion

We use daily data of the Taiwan stock market to examine whether the market timing strategy filtered by volatility delivers abnormal returns. We find that 10-day MA strategy outperforms all other longer days of MA strategy. However, we cannot identify the sources that contribute to the abnormal returns of the portfolio. To obtain more robust results, we need to provide more empirical evidence to support the validity of our proposition in the future. First of all, will different data frequency like weekly data change the results? Will the results be different if sampling period for volatility changes from one year to 6 or 3 months? Secondly, as [5] points out, we need more variables like momentum, macroeconomic condition, investor sentiment, liquidity, and among others to help us to identify the factors in explaining the abnormal returns of 10-day MA strategy. Finally, we need more risk metrics like maximum drawdown and VaR for investors in their risk management.

## References

1. Brock, W., Lakonishok, J., LeBaron, B.: Simple technical trading rules and the stochastic properties of stock returns. *J. Finan.* **47**(5), 1731–1764 (1992)
2. Covell, M.: *Trend Following: How Great Traders Make Millions in Up or Down Markets*. Prentice Hall, New York (2005)
3. Faber, M.T.: A quantitative approach to tactical asset allocation. *J. Wealth Manag.* **9**(4), 69–79 (2007)
4. French, K.R., Schwert, G., Stambaugh, R.F.: Expected stock returns and volatility. *J. Finan. Econ.* **19**(1), 3–29 (1987)



5. Han, Y., Yang, K., Zhou, G.: A new anomaly: the cross-sectional profitability of technical analysis. *J. Finan. Quant. Anal.* **48**(5), 1433–1461 (2013)
6. Henriksson, R.D., Merton, R.C.: On market timing and investment performance. II. statistical procedures for evaluating forecasting skills. *J. Bus.* **54**(4), 513–533 (1981)
7. Hibbert, A.M., Daigler, R.T., Dupoyet, B.: A behavioral explanation for the negative asymmetric return-volatility relation. *J. Bank. Finan.* **32**(10), 2254–2266 (2008)
8. Li, Q., Yang, J., Hsiao, C., Chang, Y.-J.: The relationship between stock returns and volatility in international stock markets. *J. Empirical Finan.* **12**(5), 650–665 (2005)
9. Lo, A.W., Mamaysky, H., Wang, J.: Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation. *J. Finan.* **55**(4), 1705–1765 (2000)
10. Poon, S.-H., Taylor, S.J.: Stock returns and volatility: an empirical study of the UK stock market. *J. Bank. Finan.* **16**(1), 37–59 (1992). Special Issue on European Capital Markets
11. Poterba, J.M., Summers, L.H.: The persistence of volatility and stock market fluctuations. *Am. Econ. Rev.* **76**(5), 1142–1151 (1986)
12. Santis, G.D., Ímrohoğlu, S.: Stock returns, volatility in emerging financial markets. *J. Int. Money Finan.* **16**(4), 561–579 (1997)
13. Treynor, J.L., Mazuy, K.K.: Can mutual funds outguess the market? *Harvard Bus. Rev.* **44**, 131–136 (1966)
14. Yu, H., Nartea, G.V., Gan, C., Yao, L.J.: Predictive ability and profitability of simple technical trading rules: recent evidence from Southeast Asian stock markets. *Int. Rev. Econ. Finan.* **25**, 356–371 (2013)
15. Zhu, Y., Zhou, G.: Technical analysis: an asset allocation perspective on the use of moving averages. *J. Finan. Econ.* **92**(3), 519–544 (2009)