國立政治大學國際經營與貿易學系

博士論文

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探究市場波動度資訊在技術分析中的價值
The Informational Role of Market Volatility in Technical Analysis

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中華民國一百零二年一月

謝辭

本論文承蒙恩師　郭炳伸老師與　林信助老師不辭辛勞指導，從教導我如何從事研究，訓練我如何進行有系統的邏輯思考，培育我待人處事的能力，鼓勵並期許我這隻笨鳥即便慢飛，也能飛出一片屬於自我的燦爛天空。對於兩位恩師，學生謹此至上最高敬意與謝忱。

感謝口試委員　周雨田老師、蔡文禎老師及　陳旭昇老師，提供許多寶貴的意見與對疏漏之處的匡正，使本篇論文更臻完善，謝謝老師們！

感謝致綱學長、淯靖學姐與士真如同親人般地照顧我，給予我許多協助與建議，並鼓勵我正向思考、再接再厲、繼續努力。系上助教們有如姐姐般的關懷與協助，也令我滿心感激。謝謝你們，在此致上最深的謝意！

最後感謝陪伴我的母親、公公、婆婆及家人們，特別要謝謝我的先生，沒有你的支持與鼓勵，我難以成長至今。

在此謹以此論文來獻給我的家人、好友及教育我的師長。

莊珮玲　謹誌

政治大學國際經營與貿易學系

中華民國一百零二年一月

The Informational Role of Market Volatility in Technical Analysis

Abstract

The theme of this thesis seeks to explore the value of information of market volatility in technical analysis. In the literature, the technical analysis primarily involves the use of the information of past prices and/or volumes to predict future price movements in financial assets, yet little is known about whether there exists other information that is valuable to improve the predictability of technical analysis. The possible relation between volatility and profitability of technical analysis mentioned in some studies drives us to investigate whether the information of market volatility within the framework of the technical analysis can improve our understanding toward the market price movements.

1. Does Market Volatility Improve Profitability of Technical Analysis?

This chapter first studies whether the information of market volatility is capable of yielding higher profitability. Specifically, we compare the performance of a Variable Moving Average (VMA) rule, in which market volatility plays an important role, with five other popular trading rules. When applied to the Dow Jones Industrial Average index, the Superior Predictive Ability test by Hansen (2005) shows that the VMA rule outperforms other rules with higher profitability. Second, to further investigate the origin of superior profitability, we conduct the test of Cumby and Modest (1987), and find that the VMA rule does enjoy better market timing ability. Third, we explore whether the VMA rule has differential performance in different market conditions. The results show that the market timing ability of the best VMA rule is asymmetric in bull and bear markets, and the best VMA rule outperforms the Moving Average (MA) rule and the Momentum Strategies in Volume (MSV) rule both in bull and bear markets, particular in bear markets.

2. Exploring the Information Content of Market Volatility in Technical Analysis

In this chapter, we study how market volatility information affects trading signals generated from the technical analysis. Through the use of the time-varying-transition-probability (TVTP) Markov-switching model, we find that the increase of market volatility leads to a higher probability of signals generated from the VMA rule. Moreover, such an effect is asymmetric in bull and bear markets. This chapter also reexamines the value of market volatility in the simple MA rule by comparing the trading signals produced from the Fixed-transition-probability (FTP) and the TVTP Markov-switching model. Our results show that the time to enter or exit the market affected by market volatility information will benefit investors with higher profit.

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1 Introduction

Technical analysis of financial markets involves forecasting asset prices and providing trading advices on the basis of visual examinations or certain quantitative summary measures of past price movements (Edwards and Magee, 1967; Murphy, 1986). In the literature, the technical analysis is primary based on the information of past prices and/or volumes. However, in addition to past prices and volumes, it is legitimate to question whether there exists other information that can improve the profitability of technical analysis. The study of Yamamoto (2012) shows the same thought by investigating technical rules that utilize information regarding the order-flow imbalance and order-book imbalances, although these information do not contribute to profiting in intraday trading.

LeBaron (1999) mentions that one possible factor that might drive predictability is volatility, and high volatility periods might add extra risk to dynamic strategies implying a higher risk premium, and therefore greater predictability. In the study of Owen and Palmer (2012), they found that the profits for a momentum trading strategy in the foreign exchange market exhibited a downward trend in nine countries, and this downward trend may be somewhat explained partly by the declining exchange rate volatility. The possible relationship between the volatility and the profitability motivates us to think whether the volatility is an important information in technical analysis, and whether the technical trading strategies that are formulated according to such information can yield better profit? This thesis thus aims to investigate the profitability of the trading strategies based upon the information of market volatility. Compared to previous studies, this thesis makes a unique contribution to the body of knowledge on the value of the information of market volatility in the profitability of technical analysis.

This thesis consists of two chapters. In the first chapter, we examine whether the information of market volatility can enhance the predictability of technical analysis on the Dow Jones Industrial Average (DJIA) index over 1928/10/1-2010/6/28, by the Superior Predictive Ability Test (SPA) proposed by Hansen (2005). We find strong evidence for the existence of statistically significant larger excess return to the technical trading rule formulated based upon the information of market volatility. Then we seeks to find evidence that can account for its better performance. Our results from the market timing test of Cumby and Modest (1987) clearly reveal that the technical trading rule with the information of market volatility enjoys better timings in generating profitable trading signals. Lastly, we further investigate whether the better predictive ability of the technical trading rule with market volatility is sensitive to different market conditions, We find that it outperforms other rules both in bull and bear markets, particular in bear markets.

The second chapter seeks to explore how the market volatility ratio is informationally relevant for the determination of trading signals in technical analysis by the time-varying-transition-probability (TVTP) Markov-switching model. This is the second contribution in the thesis. The technical trading rule formulated based on the information of market volatility we adopt in this thesis is the Variable Moving Average (VMA), a variant of the Moving Average (MA) system. Due to the specific trading mechanism in the MA system, the crossover, the nonlinear relationship between the market volatility and trading signals can be measured through the TVTP Markov-switching model. Our estimation results demonstrate that the increase of market volatility leads to a higher probability of generating signals in technical analysis. Furthermore, the effect is stronger in bear markets than in bull markets. While for a buying signal, its effect in bull markets is larger than in bear markets. In the second chapter, we also seek to reexamine the value of market volatility by the Fixed-transition-probability (FTP) and the TVTP Markov-switching models for a particular Simple MA rule. This idea emerges from the trading rules (with and without market volatility) chosen to be compared in our previous study are based on different parameter settings and the time they generate signals are totally different. As a result, the worth of the information of market volatility in technical analysis can not be revealed directly. Through comparing the trading signals generated from the FTP and the TVTP Markov-switching models for a particular Simple MA rule, we can clearly see how the time the signal generated varies and how much more profit investors can get after the information of market volatility is considered in forecasting. Our results reveal that the time to enter or exit the market affected by market volatility information will benefit investors with higher profitability.

2 Does Market Volatility Improve Profitability of Technical Analysis?

2.1 Introduction

Technical analysis, based on the premise that price movement will repeat itself and then display regular or recurring pattern, is a method of forecasting future price movement relying only on the information of past prices and/or volumes. This method has a long history among investment professionals (Smidt, 1965; Allen and Taylor, 1992; Billingsley and Chance, 1996; Lui and Mole, 1998; Oberlechner, 2001; Gehrig and Menkhoff, 2004; Covel, 2005; Lo and Hasanhodzic, 2009). The essence of technical analysis and its widespread adoption by practitioners conflict with the central idea of the efficient market hypothesis. Thus, whether investors can get statistically significant economic profits by technical analysis has drawn a lot of attention and discussion since Alexander (1961). Recent studies find more and more evidences of profitability of technical analysis even by examining more trading systems or adopting stricter statistical tests solving data snooping bias problems (Brock et al., 1992; Chan et al., 1996; Neely et al., 1997; Sullivan et al., 1999; LeBaron, 1999; Okunev and White, 2003; Hsu and Kuan, 2005; Schulmeister, 2008). The consensus of these studies appears that using technical analysis helps investors to forecast the market.

In addition to technical analysis, market volatility investigation is also an important issue in the financial literature and there exists a lot of papers on modeling and estimating it. Furthermore, the market volatility is viewed as the valuable information and acts as a key input in numerous financial researches such as the portfolio diversifications, the hedging strategy investigations, and the asset pricing models. Many value-at-risk models also require the estimation of volatility parameter to measure the market risk. Despite the accumulating evidence on the value of technical analysis by examining different trading systems and the increasing importance of the market volatility as a key input in financial studies, little is known about the value of market volatility in technical analysis. What is the role of market volatility playing in technical analysis? Is it valuable for enhancing the profitability of technical analysis if it is used as an input in the technical trading systems?

In this paper we are interested in examining a number of related questions. First, we ask whether market volatility is useful in enhancing the profitability of the technical analysis in which market volatility acts as an important input in the technical trading systems. We adopt the variable moving average (VMA), a variant of the popular moving average system proposed first by Chande (1992). The VMA rule automatically adjusts its effective length of the moving average according to the changing market conditions measured by the level of market volatility. It is viewed as the representative of the technical analysis comprising the information of market volatility in this study. Market volatility in the VMA rule is built to detect whether the market price makes big moves in up or down direction or whether it moves in a narrow range. In other words, market volatility here helps the moving average trading strategy to detect the market trend more timely. We apply five most tested technical trading systems (filter, moving average, support and resistance, channel breakout, and momentum strategies in volume), and compare them with the VMA rule on the Dow Jones Industrial Average (DJIA) index over 1928/10/1-2010/6/28. In order to minimize data snooping bias, the Superior Predictive Ability Test (SPA) proposed by Hansen (2005) is performed. Our SPA results both in full sample and several subsample periods clearly demonstrate that the VMA rule outperforms others with statistically significant greater profitability in the DJIA market.

Since we find strong evidence for the existence of statistically significant larger excess return to the VMA rule, we then consider what the source of the larger excess returns of the VMA rule might be. That is we want to discuss the possible reason why market volatility betters the performance of the technical analysis. For any technical trading rule to be profitable, the stock return must be predictable. The higher predictability of stock returns permits the possibility of larger excess return of technical analysis. Therefore, we carry out the market timing tests described in Cumby and Modest (1987) to examine the comparative predictability of the best VMA rule. This test can be used for investigating the ability of a trading rule to predict the sign of the one-period-ahead excess return. In this study, we modify this test by regressing the excess return to three dummy variables, which represent three forecast positions of the rule, long, short and no positions. By the modification, we can study the market timing ability of a trading rule in forecasting future price to rise or descend without losing the essence of the market timing tests. Since the VMA rule is the variant of the moving average system, we compare the market timing ability of the best VMA rule with that of the best MA rule. We also make comparisons between the market timing ability of the best VMA rule and that of the second best rule in our SPA results, which is the momentum strategies in volume (MSV) rule. There is strong evidence indicating that all of these three best rules can forecast the upward direction of future price movement well, but only the best VMA rule possesses predictive ability for future downward trends.

Moreover, we are also interested in examining whether the market timing ability of the trading rules is different due to different market conditions. In this study, different market conditions are measured by bull and bear markets, which are identified with the dating algorithm of Pagan and Sossounov (2003). Our results show that the market timing ability of the best VMA, best MA and best MSV rule are all asymmetric in different market conditions. They are good at detecting price rising trends in bull markets rather than in bear markets, while they do possess predictive ability of price decreases only for bear markets not for bull markets. Besides, the best VMA rule gains higher daily profit and suffer less daily loss as it signals long (short) and short (long) positions in bull (bear) markets, respectively. As a whole, the best VMA rule outperforms the best MA and best MSV rule both in bull and bear markets.

The remainder of the paper is organized as follows: Section 2 outlines the technical trading rules used in this study. The SPA test of Hansen (2005) is presented in Section 3. Section 4 contains the data description and the SPA results of full and several subsample periods. Section 5 provides evidence for the market timing ability of the best VMA, best MA and best MSV rule. Section 6 discusses whether these three best rules have differential performance in different market conditions, and Section 7 concludes the paper.

2.2 Technical Trading Rules

In this paper, technical analysis we adopt can be categorized into two groups, the first group is the technical analysis without the information of the market volatility, and the second one, in contrast, consolidates the market volatility to form the new moving average system. Each group of rules is explained below.

2.2.1 Static Trading Rules

For the first group, we consider five types of trading rules: filter, moving average, support and resistance (trading range break), channel breakout, and momentum strategies. These five types of rules are very popular among the practitioners on financial markets and have already drawn a lot of discussion in the literature. For the parameter values of each type of rules, we select a fairly large variety that has been applied in Sullivan et al. (1999), Hsu and Kuan (2005), and Qi and Wu (2006).

Technical trading rules, even having different mechanisms or forms, are to identify a trend reversal at a relatively early stage and then ride on that trend until there exists evidence showing that the trend has reversed. A filter rule generates a buy (sell) signal when today's closing price rises (falls) by x % above (below) its most recent low (high). The moving average rule uses n-period previous prices, including today's price, to calculate an average value. It generates a buy (sell) signal when the n-period shorter moving average moves above (below) the m-period longer moving average.

The support and resistance (trading range break) rule involves buying (selling) when the closing price rises above (falls below) the maximum (minimum) price over the previous n periods. The channel breakout rule is quite similar to the support and resistance rule. It uses the maximum and minimum price over the previous n periods to construct the channel with one limitation that is the difference between the maximum and minimum price should be within x. The channel breakout rule involves buying (selling) when the closing price moves above (below) the channel.

The momentum strategy we adopt is the momentum strategy in volume. The momentum strategy in volume has been widely analyzed in the literature. Momentum strategy's signals are determined by the oscillator and the overbought/oversold level k. It generates a buy (sell) signal as the oscillator crosses the overbought (oversold) level from below (above).

2.2.2 Dynamic Trading Rule

VMA rule In 1992, Chande proposed a variant of the moving average system, the VMA rule. The main reason that Chande proposed this rule is that the existing technical trading rules are static and not responsive enough to the changing nature of markets. Static trading rules, by the definition, are the rules that do not change the length of the historical data used for forecast future price movement. For example, an n-length simple moving average strategy means that market practitioners at each time use fixed n-length of the historical data to calculate one moving average value, and then make trading decisions based on these calculations.

The market is dynamically evolving with continuous changes; therefore, static trading rules with fixed length of data used in detecting the emergence of new trends may not work all the time. For instance, consider two simple moving averages, a shorter moving average and a longer moving average. If the market is trending, making big moves in up or down direction, the shorter moving average will response more quickly than the longer one since it gives more weight to latest data and then may generate signal earlier. If the market, on the other hand, is ranging on which price trades in a narrow range without any trend, the shorter moving average will tend to produce numerous false trading signals due to its' great proportion of more recent data, but the longer moving average desensitizes small erratic price movement and will generate fewer or no false signals.

Due to the continuous changes in the market, Chande introduces a trading rule that can adapt itself to the market condition becoming a shorter moving average as the market is trending and automatically changing into a longer one when the market is ranging. He constructs the VMA rule by revising the exponential moving average as follows:

$$\text{EMA}_t = \alpha P_t + (1-\alpha)\text{EMA}_{t-1}, \tag{1}$$

$$\alpha = \frac{2}{N+1}, \tag{2}$$

Here, EMA_t is the exponential moving average value at time t, α is the numerical constant, N is the effective length of historical data used to calculate the exponential moving average value, P_t is the closing price at time t. Equation (1) is the traditional exponential moving average in which α is referred as the smoothing parameter describing the weight that the exponential moving average gives to the more recent data. As the smoothing parameter α increases (N decreases), the exponential moving average adopts less length of historical data and has a greater proportion of the latest data; therefore, it will trace the market price more closely. In contrast, as α decreases (N increases), more length of historical data is considered, greater weight is given to the more distant data and the gap between the exponential moving average and the current price will increase.

Since α is a constant and fixed term, it does not adjust to the changing nature of market in advance. Therefore, Chande improves the smoothing parameter of the exponential moving average from constant to continuously variable by tying it to a market-related variable as below:

$$\text{VMA}_t = \alpha_t^* P_t + (1 - \alpha_t^*)\text{VMA}_{t-1}, \tag{3}$$

$$\alpha_t^* = \alpha \text{VR}_t, \tag{4}$$

$$\text{VR}_t = \frac{\sigma_t^n}{\sigma_t^{ref}}, \tag{5}$$

In Equation (3), VMA_t is the variable moving average at time t, and the smoothing parameter here is α_t^*, which is variable, consists of the constant term α and the market variable VR_t. VR_t is the market volatility ratio viewed as a market variable and is formed by σ_t^n and σ_t^{ref}. σ_t^n is the standard deviation of closing prices over past n periods at time t, σ_t^{ref} is the reference standard deviation of closing prices over some period of time longer than n at time t.

The value of the market volatility The most important part in the VMA rule is the market volatility ratio, VR_t. It is constructed in order to detect the market condition: the price action is heating up or cooling down. It acts as the automatically adjusting device for choosing more suitable effective length of the historical data. The key idea of Chande's VR_t is that if the market is active with the trend, making big moves in up or down direction, the market price will change largely. Whether the market price changes largely or not might be measured by the standard deviation of closing prices, and a reference standard deviation is needed to tell us whether the observed standard deviation is too high or too low. Thus Chande attempts to use the ratio of σ_t^n to σ_t^{ref} as the proxy of the market condition.

The information of the market volatility makes the VMA a more responsive and smarter indicator than the exponential and the simple moving average. Consider the following three situations. First, if σ_t^n is greater than σ_t^{ref}, that is $\mathrm{VR}_t > 1$, it implies that the market price over the past n periods changes more largely than before because traders over the past n periods adjust rapidly to new information. Since $\mathrm{VR}_t > 1$, the VMA will take a larger bite of the new data P_t and the effective length of the average decreases. Then the VMA will generate an earlier signal under the moving average crossover decision model. In the second situation in which σ_t^n is smaller than σ_t^{ref} ($\mathrm{VR}_t < 1$), market price over the past n periods moves in a narrow range due to no influential or new information on the market. When $\mathrm{VR}_t < 1$, the VMA takes a smaller bite out of the new data, and the effective length of the average increases. Thus the VMA will generate fewer false signals. In other words, the VMA will automatically become a shorter moving average or change into a longer one based on whether the market is active or not. Third, the VMA will become the exponential moving average when $\mathrm{VR}_t = 1$ and the effective length of moving average will be determined only by the constant term, α.

The trading strategies in the VMA For the trading strategies in the VMA, Chande mentions that all the conventional strategies with the moving average system can be extended in the VMA. The most popular trading strategies is the moving average crossover decision model as follows: [1]

[1]For the parameter values of the VMA, the settings in Chande (1992) and Chande (1994) are adopted. We also consider the suggestions of some professional traders from the websites of professional trading companies.

Buy when current price (shorter VMA) moves above the VMA (longer VMA).

Sell when current price (shorter VMA) moves below the VMA (longer VMA).

2.3 Methodology

2.3.1 Data Snooping Bias and the SPA test

In the technical analysis literature, researchers typically can create a large number of trading rules by fine-tuning the parameters of the rules, and subsequently attempt to find a trading rule that yield the maximum excess return during the sample period. The major drawback of such an approach is that it often leads to the so-called *data snooping bias*. In other words, the most profitable trading rule so identified from historical data may only stand out in the selected sample period, and does not really enjoy any predicting power of profitable opportunities (see Lo and MacKinlay 1990.)

In dealing with such data snooping bias, two major approaches are proposed in related literature. First, to avoid data-mining the same data set repeatedly, Lakonishok et al. (1994), and Chan et al. (1998) suggest using different but comparable samples to examine profitability of trading rules. Such an approach may not work if no comparable samples are available. In that case, Brock et al. (1992), Gencay (1998), and Rouwenhorst (1999) propose to test for the profitability of trading rules not only for the entire long sample period, but also for many sub-periods. Again, for adopting such an approach, one often needs to worry about how to split the long sample in an objective and convincing way. Second, to control for the test size, Lakonishok and Smidt (1988) apply the *Bonferroni inequality* in testing all possible models. Such an approach may present a practical difficulty in the case of technical analysis, as there exist too many trading rules to be considered. Along the same spirit of Lakonishok and Smidt (1988), White (2000) proposes the *Reality Check* (RC), which is capable of dealing with the data snooping bias, and handling a large number of trading rules at the same time. There are, however, two shortcomings of the RC: the average return in the RC are not standardized; and the RC fail to exclude trading rules that do not produce positive returns, which reduces the test power of the RC statistic. Consequently, Hansen (2005) proposed a more powerful *Superior Predictive Ability* (SPA) test with the following null hypothesis,

$$H_0^{SPA} \;:\; \mu \leq 0, \tag{6}$$

$$\text{where} \qquad \mu = \max_{k=1,...,L}\{E(R_k)\},$$

$$E(R_k) = \bar{R}_k = N^{-1}\sum_{t=p}^{T}\bar{R}_{k,t}, k = 1, ..., L,$$

k is the k^{th} trading rule; L is the total number of trading rules; R_k denotes the return of the k^{th} trading rule; T is the sample size; $N \equiv T - p + 1$ denotes total usable number of observations used in calculating the average returns; $E(R_k)$ is an $L \times 1$ vector, and represents average returns of L different trading rules, with 0 denoting average return of the benchmark trading rule. Rejection of the null hypothesis represents that there exists at least one trading rule whose average return is significantly greater than zero.

To implement the hypothesis testing, Hansen (2005) constructs the following test statistic

$$T_L^{SPA} = \max_{k=1,...,L}\{\frac{\sqrt{N}(\bar{R}_k)}{\widehat{\omega}_k}, 0\}, \tag{7}$$

where $\widehat{\omega}_k$ represents the standard error of trading rule k . Furthermore, Hansen (2005) propose using the stationary bootstrap to come up with the empirical distribution of T_L^{SPA}

$$T_{L,b}^{SPA*} \;=\; \max_{k=1,...,L}\{\frac{\sqrt{N}(\hat{\mu}_{k,b,t}^{*c})}{\widehat{\omega}_k}, 0\}, b = 1, ..., B, \tag{8}$$

$$\text{where} \qquad \hat{\mu}_{k,b,t}^{*c} = \bar{R}_{k,b}^{*} - \bar{R}_k 1\left(\bar{R}_k \geq -\sqrt{\frac{\widehat{\omega}_k^2}{\sqrt{N}}2\log\log N}\right),$$

B is the total numbers of re-sampling; $1(\cdot)$is an indicator function, which is equal to 1 when the condition inside the indicator function is satisfied, and is equal to 0 otherwise; $\sqrt{2\log\log N}$ is the threshold rate. As long as the p-value of the test statistic is smaller than the significance level, we reject the null hypothesis, and hence there exists at least one trading rule with significantly positive average return.

2.4 Empirical Results on the Trading Rule Profitability

2.4.1 Data

Data examined in this paper consists of the Dow Jones Industrial Average (DJIA) daily closing price from Oct 1, 1928 to June 28, 2010 - a collection of more than 80 years of daily data. In addition to the full sample, we also conduct sub-sample analysis as a robustness check. To create sub-samples, two criteria are adopted. First, we divide the full sample into two sub-samples with equal lengths according to Qi and Wu (2006). Second, based on Brock et al. (1992), the full sample is split into the following five sub-samples: 1928/10/1−1938/12/31, 1939/1/1−1962/6/30, 1962/7/1−1986/12/31, 1987/1/1−1996/12/31, and 1997/1/1−2010/6/28. Table 1 reports some summary statistics for daily changes in the logarithm of DJIA index both for the full and sub-samples. We observe that the DJIA daily return distributions exhibit excess kurtosis for the full and all sub-samples, and some of them are even strongly leptokurtic.

The return of the k^{th} technical trading rule at time t, $R_{k,t}$, is evaluated as follows:

$$\begin{aligned} &R_{k,t} = (lnP_t - lnP_{t-1}) \cdot I_{k,t-1} - |I_{k,t-1} - I_{k,t-2}| \cdot g, \\ &k = 1, ..., L, t = 256, ..., T, \end{aligned} \tag{9}$$

where P_t is the DJIA closing price at time t; I_t is a dummy variable, which is equal to 1 representing a long position, 0 representing a neutral position, and -1 standing for a short position; g is the one-way transaction cost. Here we set g equal 0.05%, a round-trip transaction cost is therefore 0.1%; L describes the total number of the technical trading rule we apply in this study, which is 5,162 in this study; t starts from 256 because some trading rules need 255 days of historical data to generate a trading signal, and T is the sample size, which is 20,526 for the full sample.

2.4.2 SPA Test Results: Full Sample and Sub-samples

In this subsection, we present the SPA test results on the profitability of 5,162 technical trading rules. Table 2 reports the performance of the best trading rule on each trading family in the full sample with the one-way transaction cost 0.05%. The first and second columns in Table 2 are

Table 1: Descriptive Statistics for Daily Changes in the Logarithm of DJIA index

This table reports summary statistics for daily return of DJIA index (in %) in the full and sub-sample periods. The full sample period is between Oct 1, 1928 and June 28, 2010, with 20,526 observations. We have two types of sub-sample period. One is built according to Qi and Wu (2006), while another one is based on the criterion of Brock et al. (1992). Here $\rho(k)$ is the k^{th} order serial correlation of daily return. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

	Full	Qi and Wu		Brock et al.				
		Sub-sample 1	Sub-sample 2	Sub-sample 1	Sub-sample 2	Sub-sample 3	Sub-sample 4	Sub-sample 5
Sample Size	20,526	10,263	10,263	2,558	5,888	6,157	2,529	3,394
Mean	0.018	0.012	0.024	-0.017	0.022	0.019	0.048	0.013
Max	14.273	14.273	10.508	14.273	9.090	4.952	9.666	10.508
Min	-25.632	-14.470	-25.632	-14.470	-7.043	-4.718	-25.632	-8.201
Standard Deviation	1.165	1.239	1.085	2.118	0.783	0.842	1.066	1.276
Skewness	-0.595	-0.103	-1.312	0.030	-0.680	0.260	-5.710	-0.088
Kurtosis	27.707	19.817	39.862	8.698	13.873	5.273	142.523	10.039
$\rho(1)$	0.016 **	0.014	0.017	-0.027	0.118 ***	0.145 ***	0.016	-0.067 ***
$\rho(2)$	-0.026 ***	-0.008	-0.050 ***	0.003	-0.056 ***	-0.001 ***	-0.077 ***	-0.063 ***
$\rho(3)$	0.014 ***	0.018	0.010 ***	0.016	0.015 ***	-0.003 ***	-0.02 ***	0.042 ***
$\rho(4)$	0.012 ***	0.034 ***	-0.017 ***	0.029	0.049 ***	-0.003 ***	-0.052 ***	-0.003 ***
$\rho(5)$	0.005 ***	0.014 ***	-0.007 ***	0.013	0.018 ***	-0.012 ***	0.065 ***	-0.038 ***
$\rho(6)$	-0.024 ***	-0.038 ***	-0.006 ***	-0.044	-0.028 ***	-0.020 ***	-0.002 ***	0.005 ***

the best rules on each trading family, and their rank in the universe of trading rules. The third, fourth, and fifth columns are their total number of trades, daily mean return and annualized return they obtain in this period. The last column reports the $p-$value of SPA test. We can observe that the overall best rule in the universe is the VMA family, and the best rule of the MSV wins the third place. The annual profits are 8.18%, 7.64%, 7.04%, 6.67%, 4.98%, and 2.64%, respectively, for the best rule of the VMA, MSV, MA, FR, CB, and the SR families. The best rule of the VMA, MSV, MA and FR families enjoy statistically significant profit at the 10% significant level, while profits from other two type of rules are all insignificant different from 0. To sum up the SPA test results for the full sample, as presented in Table 2 , we find that the VMA rule can earn statistically and economically significant profit, and it outperforms others with highest mean return.

Table 3 describes the performance of the best rule on each trading family in the sub-samples. Panel A and B demonstrate the results in the first and second sub-sample, respectively. Similarly, the best rule in the universe in these two sub-samples are all the VMA rules. It has economically significant profitability due to its SPA $p-$value less than 5% in the first sub-sample. Except for the best rule of the VMA and MSV, other rules are insignificantly profitable in the first sub-sample. And in the second sub-sample, the profitability of all types of rule is weaker. We reject the null hypothesis for the performance of the best rule on the VMA family only at the 10% significant level.

Table 4 summarizes the performance of the technical trading rules in other five sub-samples. We just report the best one in the universe of 5,162 trading rules in each sub-sample with its annualized return and the SPA $p-$value. We can discover that three out of five best rules in these periods are the VMA rules (Sub-sample 2, 3, and 4), and the null hypothesis of the SPA test for Sub-sample 2 and 3 can be rejected even at 1% significant level. Although the best one in the Sub-sample 1 and 5 are the MSV rule, their profitability are all insignificant.

To conclude the SPA results both for the full sample and all sub-samples, we can find that the performance of the VMA is more outstanding than other five rules. Besides, these results provide us the evidence that the information of market volatility does enhance the profitability of the Moving Average system, as presented in Table 2 and Table 3. In the full and the two sub-samples, the best rules of the VMA are the entire best one in the universe of 5,162 trading rules, while the best rules of the MA in these periods merely win 7th, 13th, and 10th places in the universe, respectively.

Table 2: The Performance of the Best Trading Rule in the Full Sample

This table presents the SPA test results on the profitability of 5,162 technical trading rules for the period between Oct 1, 1928 and June 28, 2010. We report the performance of the best trading rule in each trading family with their ranking in the universe of 5,162 rules, the number of trades, daily and annualized return they obtain with one-way transaction cost 0.05% , and their p-value on the SPA test. There are two signals, long and short, in one trade; therefore, the total trading number of the best VMA rule is 563 indicating that it has 1,126 signals. Daily return is computed from dividing the cumulative return in this period by the sample size (20,526 days). Annual return is calculated by multiplying the daily return by 252 because we have 252 trading days per annum. SPA (C) is the SPA $p-$ value. * denotes significance at the 10% level, **denotes significance at the 5% level, and *** denotes significance at the 1% level.

Best Trading Rule in Each TA Family	Rank	Number of Trades	Daily Return	Annualized Return	SPA (C)
VMA[a]	1	563	0.0325%	8.18%	0.006 ***
MSV[b]	3	400	0.0303%	7.64%	0.020 **
MA[c]	7	49	0.0279%	7.04%	0.050 *
FR[d]	11	23	0.0265%	6.67%	0.092 *
CB[e]	141	1878	0.0198%	4.98%	0.492
SR[f]	988	410	0.0105%	2.64%	0.742

Note:

[a]The best rule on the VMA family: $\alpha = 0.049$ (N = 40)、$\sigma_t^{15,n}$、$\sigma_t^{30,ref}$、0.0005 band.

[b]The best rule on the MSV (Momentum Strategy in Volume) family: 2-day moving average、250-day ROC、0.15 overbought/oversold rate、50 fixed holding days.

[c]The best rule on the MA family: 10-day short-run moving average、250-day long-run moving average、0.001 band.

[d]The best rule on the FR family: 0.05 filter rate、the highest and lowest price over the 2 most recent days.

[e]The best rule on the CB family: the high price over previous 5 days is within 0.01 of the low price over previous 5 days、0.0005 band、10 fixed holding days.

[f]The best rule on the SR family: the maximum(minimum) price over the previous 50 days by band 0.01、10 fixed holding days.

Table 3: The Performance of the Best Trading Rule in the Sub-Samples

This table reports the SPA test results on the profitability of 5,162 technical trading rules in two sub-samples as a robustness check. The criterion used to create sub-samples is based on Qi and Wu (2006). Panel A and B demonstrate the performance of the best trading rule in each trading family with one-way transaction cost 0.05% in the first and second sub-sample, respectively. * denotes significance at the 10% level, **denotes significance at the 5% level, and *** denotes significance at the 1% level.

Best Trading Rule in Each TA Family	Rank	Number of Trades	Daily Return	Annualized Return	SPA (C)
Panel A: Sub-sample 1, 1928/10/01-1969/10/28					
VMA	1	870	0.0515%	12.97%	0.008 ***
MSV	4	198	0.0430%	10.83%	0.077 *
MA	13	583	0.0399%	10.06%	0.120
CB	39	933	0.0341%	8.60%	0.400
FR	138	1775	0.0294%	7.40%	0.670
SR	259	583	0.0262%	6.61%	0.848
Panel B: Sub-sample 2, 1969/10/29-2010/06/28					
VMA	1	306	0.0310%	7.82%	0.090 *
MSV	2	141	0.0287%	7.23%	0.170
CB	4	391	0.0268%	6.75%	0.400
MA	10	108	0.0249%	6.28%	0.848
FR	25	1105	0.0237%	5.97%	0.910
SR	1169	156	0.0075%	1.89%	1

Table 4: The Performance of the Best Trading Rule in Other Five Sub-Samples

This table reports the performance of the best one in the universe of 5,162 technical trading rules in each sub-sample. Five sub-samples are created by the measure taken in Brock et al. (1992). The annualized return of the best rule is calculated with one-way transaction cost 0.05%. SPA (C) is the SPA $p-$ value. * denotes significance at the 10% level, **denotes significance at the 5% level, and *** denotes significance at the 1% level.

Sub-sample	the Best Rule in Each Sub-sample	Annualized Return	SPA (C)
Sub-sample 1	MSV	29.12%	0.428
Sub-sample 2	VMA	10.79%	0.004 ***
Sub-sample 3	VMA	13.55%	0.000 ***
Sub-sample 4	VMA	12.39%	0.186
Sub-sample 5	MSV	13.08%	0.654

2.5 Market Timing Ability Test

We have shown that investors can get higher excess return by the VMA rule, and now we turn to finding the reason possibly explaining its higher profitability. If a technical trading rule can be profitable, the stock return must be predictable. Higher profitability of a trading rule might stem from that it possesses higher predictive ability for stock returns.

Tests of market timing ability are common ways to evaluate whether a forecast is to have value or not in financial literature. These tests are regularly used to study whether mutual fund managers, portfolio managers, investment newsletter recommendations or trading rules' signals offer any market timing ability (Henriksson, 1984; Cumby and Modest, 1987; Lee and Rahman, 1990; Graham and Harvey, 1996; Kho, 1996; Kleiman et al., 1996; Daniel et al., 1997; Neely and Weller, 1999; Bollen and Busse, 2001). For any trading rule, timing implies that excess returns are positive after its recommended long positions and negative after its recommended short positions. In other words, the forecasting ability of a trading rule can be evaluated by these tests.

In this study, we apply the market timing ability tests by Cumby and Modest (1987) since it is often used for investigating whether a trading rule can predict the sign of a one-period-ahead excess return.[2] This test is carried out by regressing excess returns on one forecast position measured by an indicator variable z, which is either + 1 or - 1, depending upon whether the trading rule signals a long or a short position. If a trading rule does possess forecasting ability, a significantly positive relation between the one-period-ahead excess return and the forecast position can be found.

We extend the test of Cumby and Modest (1987) by studying forecasting ability of long positions and short positions separately and including the no-positions variable. By this extension, in addition to the market timing ability of long positions and short positions, we can also study the average direction of price changes when a trading rule recommends not to have any position. Since the VMA rule is the variant of the Moving Average system, we focus on comparing the forecasting ability of the best VMA rule with that of the best MA rule. Besides, we also make comparisons between the market timing ability of the best VMA rule and that of the best MSV rule, because the MSV rule is the second best in our previous SPA tests.

In order to carry out a reliable hypothesis testing, in which the market timing ability of the best VMA rule is compared with that of the best MA and best MSV rule, we apply the *Seemingly Unrelated Regressions* (SUR). We consider the specification of a system of three equations, each with three explanatory variables and 20,496 observations.[3] The SUR model is as follows:

$$\triangle \log P = X_i \beta_i + e_i, \ i = \text{VMA, MA, MSV}, \tag{10}$$

$$y = \begin{bmatrix} y_{\text{VMA}} \\ y_{\text{MA}} \\ y_{\text{MSV}} \end{bmatrix}, \ X = \begin{bmatrix} X_{\text{VMA}} \\ X_{\text{MA}} \\ X_{\text{MSV}} \end{bmatrix}, \ \beta = \begin{bmatrix} \beta_{\text{VMA}} \\ \beta_{\text{MA}} \\ \beta_{\text{MSV}} \end{bmatrix}, \ e = \begin{bmatrix} e_{\text{VMA}} \\ e_{\text{MA}} \\ e_{\text{MSV}} \end{bmatrix}, \tag{11}$$

[2]The assumption that relative risk premiums are constant over the sample period is made in this study.

[3]Here we delete the first 30 observations since all of these three best rules need at least 30 days to generate trading signals.

$$\text{where} \qquad X_i = (z_{1i}, z_{2i}, z_{3i}),$$

$$z_{1i,t} = \begin{cases} 1 & \text{if no position is held by the } i^{th} \text{ rule at time } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$z_{2i,t} = \begin{cases} 1 & \text{if the short position is held by the } i^{th} \text{ rule at time } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$z_{3i,t} = \begin{cases} 1 & \text{if the long position is held by the } i^{th} \text{ rule at time } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$\beta_i = (\beta_{1i}, \beta_{2i}, \beta_{3i})',$$

For each i, $\triangle \log P$ is 20,496 $\times$ 1, X_i is 20,496 $\times$ 3 and β_i is 3 $\times$ 1. The dependent variable, $\triangle \log P$, is the log return of the DJIA (multiplied by 100), and it can also be interpreted as the daily one-period-ahead excess return. The independent variables for each i are three forecast variables as follows, $z_{1i,t}$, $z_{2i,t}$ and $z_{3i,t}$. They are set to one when the i^{th} rule recommends no position, a short position, and a long position respectively; otherwise, they are zero. The sum of these three dummy variables at time t is one. β_{1i}, β_{2i} and β_{3i} are slope coefficients for the i^{th} rule.

If the i^{th} rule does possess ability to detect future downward and upward trends, β_{2i} and β_{3i} will be significantly negative and positive, respectively. A positive β_{2i} (negative β_{3i}) denotes that the i^{th} rule predicts there will be a downward (upward) trend in the future, but the actual price rises (falls). Further, we can interpret the value of β_{2i} (β_{3i}) as the mean profit/loss per day over the period in which the i^{th} rule signals short (long) positions. Then β_{1i} can be explained as the mean price change as the i^{th} rule recommends not to have any position. In Panel A of Table 5, we present the estimation results for the SUR model along with the Newey-West (1987) robust standard errors. First of all, there is strong evidence indicating that the best VMA rule does have predictive ability for both upward and downward price movements, while the best MA and best MSV rule are only capable of detecting upward price movements. We also compare the mean profit per day based on signals of long position and short-position issued by the best VMA rule, the best VMA rule, and the best MSV rule. The Wald test results in Table 6 show that the mean profit the best VMA rule gains from its long positions is significantly greater than those of the others. Its mean profit over the short-position periods is significantly greater than that of the best MSV rule, while there is no significant difference in the average short-position profit between the best VMA rule and the best MA rule.

In addition to mean profits over the short-position periods and the long-position periods for the three competing rules (based on the size and value of β_2 and β_3), we also compute the mean profit per day (MPPD) as follows:

$$\text{MPPD}_i = w_{li}^* \beta_{3i} - w_{si}^* \beta_{2i}, \tag{12}$$

where w_{li}^* and w_{si}^* for each rule are the proportion of time spent on long positions and on short positions relative to the entire sample period, respectively. Essentially, the MPPD can be interpreted as an overall performance measure of a trading rule, which is weighted by the proportions of time spent on long positions and short positions. The results are reported in Panel B and C of Table 5. All of those three rules have significantly positive mean profit per day. Furthermore, the best VMA rule earns more than the others, as presented in Table 6.

To summarize, the fact that the best VMA can predict both upward and downward price movements, while other competing rules are only capable of detecting upward price movement give a strong evidence that higher profitability of the VMA rule might just stems from its better forecasting ability of stock returns. In addition, the results that the time the best VMA spent in the market is the least (roughly 63.6%), while the mean profit it gains in the market is the most (see Table 6), offer another piece of evidence that the best VMA rule does enjoy a better timing in generating profitable trading signals.

Table 5: Cumby-Modest market timing tests for the best VMA, best MA and best MSV rule

We carry out Cumby-Modest market timing tests by applying *Seemingly Unrelated Regressions* (SUR) as follows:

$$\triangle \log P = X_i\beta_i + e_i,\ i = \text{VMA, MA, MSV},$$

where $X_i = (z_{1i}, z_{2i}, z_{3i})$ and $\beta_i = (\beta_{1i}, \beta_{2i}, \beta_{3i})'$. For each equation i, the dependent variable $\triangle \log P$, is the log return of the DJIA (multiplied by 100). The independent variables, $z_{1i,t}$, $z_{2i,t}$ and $z_{3i,t}$, are three dummy variables. They are set to one when the i^{th} rule recommends no position, a short position, and a long position respectively; otherwise, they are set to zero. β_{1i}, β_{2i} and β_{3i} are slope coefficients for the i^{th} rule. We use w_l^* and w_s^*, the proportion of the time spent long and short to the full sample period, to measure a trading rule's overall performance, the mean profit per day (MPPD). Panel A reports the regression results for the best VMA, best MA and best MSV rule, respectively. Panel B presents their overall performances. The w_l^* and w_s^* of each rule is reported in Panel C. In the parentheses are the Newey-West (1987) robust standard errors. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Position	Coefficient	i = VMA	i = MA	i = MSV
Panel A: Regression slopes				
No Position	β_{1i}	0.020	0.008	-0.003
		(0.01)	(0.01)	(0.06)
Short Position	β_{2i}	-0.117 ***	-0.057	-0.023
		(0.02)	(0.04)	(0.02)
Long Position	β_{3i}	0.105 ***	0.041 ***	0.039 ***
		(0.01)	(0.01)	(0.01)
Panel B: The overall trading performance				
Mean profit per day (MPPD_i)	$w_{li}^*\beta_{3i} - w_{si}^*\beta_{2i}$	0.070 ***	0.029 ***	0.033 ***
		(0.01)	(0.01)	(0.01)
Panel C: Weights adopted in the MPPD_i				
The time spent long/Full sample size	w_{li}^*	0.382	0.543	0.651
The time spent short/Full sample size	w_{si}^*	0.254	0.126	0.324
The total trading time/Full sample size	w_i	0.636	0.669	0.975

Table 6: Comparisons in the trading performances of the best VMA, best MA and best MSV rule

This table reports comparisons between the trading performances of the best VMA rule and that of the best MA and best MSV rule. For the i^{th} rule, the value of β_{2i} and β_{3i} can be interpreted as the mean profit/loss per day over its short-position periods and long-position periods, while β_{1i} is the average excess return when there is no signal released by this rule. The MPPD$_i$ measures its mean profit per day. These comparisons are implemented by the Wald test based on the Newey-West (1987) covariance matrix. In the parentheses are the Newey-West (1987) robust standard errors. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Position	Comparison	i = VMA, j = MA	i = VMA, j = MSV
No Position	$\beta_{1i} - \beta_{1j} = 0$	0.012	0.023
		(0.02)	(0.06)
Short Position	$\beta_{2i} - \beta_{2j} = 0$	-0.060	-0.093 ***
		(0.04)	(0.03)
Long Position	$\beta_{3i} - \beta_{3j} = 0$	0.064 ***	0.066 ***
		(0.01)	(0.01)
Overall Performance	$(w^*_{li}\beta_{3i} - w^*_{si}\beta_{2i}) - (w^*_{lj}\beta_{3j} - w^*_{sj}\beta_{2j})$	0.040 ***	0.037 ***
	MPPD$_i$ − MPPD$_j$	(0.01)	(0.01)

2.6 Is the Profitability of the Trading Rule Asymmetric in Different Market Conditions?

In the previous section, we have demonstrated a close connection between the VMA rule's higher profitability and its better forecasting ability for stock returns. This entails two interesting questions. First, is the predictive ability of the VMA rule for future price movements sensitive to different market conditions? Second, if so, does the VMA rule still enjoy higher profitability in all market conditions?

To describe the evolution of the market condition, cyclical variations in stock returns have been widely reported (Turner et al., 1989; Hamilton and Lin, 1996; Perez-Quiros and Timmermann, 2000; Perez-Quiros and Timmermann, 2001.) Typically, bull markets and bear markets are commonly adopted to characterize equity cycles (Fabozzi and Francis, 1979; Hardouvelis and Theodossiou, 2002; Guidolin and Timmermann, 2005; Chen, 2007; Jansen and Tsai, 2010.) As a stylized fact, bull markets are usually associated with higher average stock returns, and a lower variance; while bear markets are associated with lower average, but a more volatile stock returns. Specifically, we are interested in investigating whether the profitability of the VMA rule in bull markets is significantly different from that in bear markets? If the profitability of the VMA rule in bear markets is significantly higher, it may imply that the information of market volatility in bear markets is more crucial for technical trading rules to forecast future price movements.

In this study, the dating algorithm proposed by Pagan and Sossounov (2003) is used to identify bull markets and bear markets in the DJIA daily index.[4,5] According to Pagan and Sossounov (2003), a bull market occurs during the period when the stock price rises from a trough point and ends in a peak point; while a bear market exists during the period as the stock price moves from a peak point to a trough point. With this dating algorithm, all possible peaks and troughs in the DJIA index can be found and subsequently be used to identify bull markets and bear markets. Table 7 presents a summary of all bull markets and bear markets so identified. There are 23 and 22 mutually exclusive and exhaustive bull markets and bear markets. We can find that, on average, durations of bull markets tend to be longer than those of bear markets in the DJIA. Specifically, Bull markets have lasted for an average of 28 months (583 days), while bear markets have lasted for 15 months (324 days). Table 7 also shows that bull markets are associated with higher but more stable stock returns while bear markets are associated with low but volatile stock returns. These results are coincident with the findings in the literature.

2.6.1 Market Timing Ability in Bull and Bear Market

To ascertain whether the VMA rule has asymmetric, yet still dominating, performance over the equity cycles, the test of Cumby and Modest (1987) introduced in Section 2.5 is applied here again with the number of independent variables for each rule X_i extended from three to six as

[4]The dating algorithm of Pagan and Sossounov (2003) is presented in the Appendix.

[5]The original parameter settings in Pagan and Sossounov's dating algorithm are suitable for monthly data. In order to apply this algorithm to daily data, we revise the parameters based on the premise that there is 21 trading days in one month.

Table 7: Bull and bear markets in the DJIA daily price index

This table reports a summary of the bull and bear markets identified with Pagan and Sossounov (2003) algorithm over the full sample period. In the "Days" and "Duration" columns, we record the number of days for the whole bull and bear markets and the average days a bull or a bear market lasts.

Market	Definition	Number	Days	Duration	log Return, Mean	log Return, S.D.
Bull	Trough to peak	23	13,407	583	0.094	1.012
Bear	Peak to trough	22	7,119	324	-0.124	1.397

follows:

$$X_i = (z_{1i}^{bl}, z_{2i}^{bl}, z_{3i}^{bl}, z_{1i}^{br}, z_{2i}^{br}, z_{3i}^{br}), \quad i = \text{VMA, MA, MSV}, \tag{13}$$

where the superscript bl and br represent bull and bear markets in the DJIA; z_{1i}^{bl}, z_{2i}^{bl} and z_{3i}^{bl} are dummy variables of the i^{th} rule in bull markets, which are set to one when the i^{th} rule in bull markets recommends no position, a short position, and a long position respectively; otherwise, they are set to zero; similarly, z_{1i}^{br}, z_{2i}^{br} and z_{3i}^{br} are the corresponding dummy variables for the i^{th} rule in bear markets. Correspondingly, $\beta_{1i}^{bl}, \beta_{2i}^{bl}, \beta_{3i}^{bl}, \beta_{1i}^{br}, \beta_{2i}^{br}$ and β_{3i}^{br} are the associated slope coefficients for the i^{th} rule. If the i^{th} rule can forecast future price increases (decreases) in all market conditions, β_{3i}^{bl} and β_{3i}^{br} (β_{2i}^{bl} and β_{2i}^{br}) should be significantly positive (negative). We also use MPPD to measure the overall trading performance of the rule.

Table 8 reports the results of Cumby-Modest market timing tests for the best VMA, best MA and best MSV rule in bull markets and bear markets. According to the estimated results, the predictive ability of the best VMA rule for price movements is indeed asymmetric in bull and bear markets. It can forecast price increases in bull markets, but not in bear markets. Conversely, it is capable of detecting downward price actions in bear markets but not in bull markets. For the best MA and the best MSV rule, the asymmetry in their respective forecasting ability under different market conditions still exists, and is similar to that in the best VMA rule. Moreover, they incur losses significantly on average as they forecast price increases in bear markets and price decreases in bull markets.

As reported in Table 9, the profitability, measured by the MPPD, of the best VMA rule in bull and bear markets are all significantly higher than those of the best MA and the best MSV rule. This answers our second question. In other words, the higher profitability of the best VMA rule is not sensitive to different market conditions. In bull markets, the mean profit from the long positions signaled by the best VMA rule is significantly higher, and the mean loss entailed from its short-position signals is significantly less than the other two trading rules. In bear markets, although there is no significant difference between the mean profit in the downward forecasting of the best VMA rule and those of the others, the best VMA rule has significant less mean loss in the upward prediction.

It is noteworthy that, in bear markets, the mean profit of the best MA rule and the best MSV rule are not significantly different from 0, while the mean profit of the best VMA rule is significantly positive. as shown in Panel B of Table 8. This offers another piece of evidence that, when asset prices change rapidly or drastically on the market, technical trading rules which do not incorporate any market volatility information cannot respond enough to the changing market conditions. Therefore, our results suggest the information of market volatility in this kind of market should be seriously considered in technical trading rules. Another interesting result in Table 10 is that the trading performance of the best VMA rule in bear markets is better than that in bull markets. As mentioned before, better profitability of the VMA rule in bear markets may imply that the device for detecting price movements, the market volatility ratio, is particularly suitable for bear markets.

Table 8: Cumby-Modest market timing tests for the best VMA, best MA and best MSV rule in bull and bear markets

The market timing test for the trading rules in bull and bear markets is carried out by *Seemingly Unrelated Regressions* (SUR) as follows:

$$\triangle \log P = X_i \beta_i + e_i, \; i = \text{VMA, MA, MSV},$$

where $X_i = (z_{1i}^{bl}, z_{2i}^{bl}, z_{3i}^{bl}, z_{1i}^{br}, z_{2i}^{br}, z_{3i}^{br})$ and $\beta_i = (\beta_{1i}^{bl}, \beta_{2i}^{bl}, \beta_{3i}^{bl}, \beta_{1i}^{br}, \beta_{2i}^{br}, \beta_{3i}^{br})'$. For each equation i, the dependent variable, $\triangle \log P$, is the log return of the DJIA (multiplied by 100). The market conditions, bull and bear markets, are represented by the index bl and br. The independent variables, $z_{1i,t}^{bl}$, $z_{2i,t}^{bl}$ and $z_{3i,t}^{bl}$, ($z_{1i,t}^{br}$, $z_{2i,t}^{br}$ and $z_{3i,t}^{br}$), are dummy variables for bull (bear) markets. They are set to one when the i^{th} rule in bull (bear) markets recommends no position, a short position, and a long position respectively; otherwise, they are set to zero. β_{1i}^{bl}, β_{2i}^{bl} and β_{3i}^{bl} (β_{1i}^{br}, β_{2i}^{br} and β_{3i}^{br}) are the associated slope coefficients for the i^{th} rule in bull markets. Panel A reports the regression results and trading performances for these three best rules in bull markets while the corresponding results in bear markets are presented in Panel B. We use w_l^* and w_s^* to measure the trading performance of the rule, the mean profit per day (MPPD). w_l^{*bl} (w_s^{*bl}) is defined as the proportion of the time spent long (short) to all bull periods, while w_l^{*br} (w_s^{*br}) is the ratio the trading rule spent for long (short) positions to all bear periods. The results are reported in Panel C on next page. In the parentheses are Newey-West (1987) robust standard errors. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Position	Coefficient	i = VMA	i = MA	i = MSV
Panel A: Bull markets				
No Position	β_{1i}^{bl}	0.077 ***	0.105 ***	0.062
		(0.01)	(0.02)	(0.06)
Short Position	β_{2i}^{bl}	0.026	0.166 ***	0.098 ***
		(0.03)	(0.05)	(0.02)
Long Position	β_{3i}^{bl}	0.123 ***	0.080 ***	0.093 ***
		(0.01)	(0.01)	(0.01)
Overall Performance	$w_{li}^{*bl}\beta_{3i}^{bl} - w_{si}^{*bl}\beta_{2i}^{bl}$	0.059 ***	0.040 ***	0.041 ***
	(MPPD_i^{bl})	(0.01)	(0.01)	(0.01)
Panel B: Bear markets				
No Position	β_{1i}^{br}	-0.078 ***	-0.098 ***	-0.289 *
		(0.02)	(0.02)	(0.17)
Short Position	β_{2i}^{br}	-0.195 ***	-0.207 ***	-0.157 ***
		(0.03)	(0.05)	(0.03)
Long Position	β_{3i}^{br}	-0.016	-0.107 ***	-0.094 ***
		(0.03)	(0.02)	(0.02)
Overall Performance	$w_{li}^{*br}\beta_{3i}^{br} - w_{si}^{*br}\beta_{2i}^{br}$	0.090 ***	0.010	0.019
	(MPPD_i^{br})	(0.01)	(0.01)	(0.02)

Table 8 Continued

Measurement	Weight	i = VMA	i = MA	i = MSV
Panel C: Weights adopted in measuring a technical trading rule's performance				
Bull market				
The time spent long/All bull periods	w_{li}^{*bl}	0.511	0.658	0.709
The time spent short/All bull periods	w_{si}^{*bl}	0.138	0.077	0.261
The total trading time/All bull periods	w_{i}^{bl}	0.649	0.735	0.970
Bear market				
The time spent long/All bear periods	w_{li}^{*br}	0.141	0.327	0.544
The time spent short/All bear periods	w_{si}^{*br}	0.473	0.217	0.443
The total trading time/All bear periods	w_{i}^{br}	0.614	0.544	0.987

Table 9: Comparisons in the trading performances of the trading rules in each market condition

This table reports comparisons between the trading performances of the best VMA rule and that of the best MA and best MSV rule in bull and bear markets, respectively. Bull and bear markets are represented by the index bl and br. For the i^{th} rule, the value of β_{2i}^{bl} and β_{3i}^{bl} (β_{2i}^{br} and β_{3i}^{br}) can be interpreted as the mean profit/loss over its short-position periods and long-position periods in bull (bear) markets, while β_{1i}^{bl} (β_{1i}^{br}) is the average excess return over the no-position periods in bull (bear) markets. MPPD_i^{bl} (MPPD_i^{br}) measures the mean profit per day the i^{th} rule gains in bull (bear) markets. These comparisons are implemented by the Wald test based on the Newey-West (1987) covariance matrix. The Newey-West (1987) robust standard errors are in the parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Position	Comparison	i = VMA, j = MA	i = VMA, j = MSV
Panel A: Bull market			
No Position	$\beta_{1i}^{bl} - \beta_{1j}^{bl} = 0$	-0.029 (0.02)	0.015 (0.06)
Short Position	$\beta_{2i}^{bl} - \beta_{2j}^{bl} = 0$	-0.140 ** (0.05)	-0.071 ** (0.03)
Long Position	$\beta_{3i}^{bl} - \beta_{3j}^{bl} = 0$	0.043 *** (0.01)	0.030 ** (0.01)
Overall Performance	$(w_{li}^{*bl}\beta_{3i}^{bl} - w_{si}^{*bl}\beta_{2i}^{bl}) - (w_{lj}^{*bl}\beta_{3j}^{bl} - w_{sj}^{*bl}\beta_{2j}^{bl})$ $\text{MPPD}_i^{bl} - \text{MPPD}_j^{bl}$	0.019 ** (0.01)	0.019 * (0.01)
Panel B: Bear market			
No Position	$\beta_{1i}^{br} - \beta_{1j}^{br} = 0$	0.020 (0.03)	0.212 (0.17)
Short Position	$\beta_{2i}^{br} - \beta_{2j}^{br} = 0$	0.012 (0.06)	-0.038 (0.04)
Long Position	$\beta_{3i}^{br} - \beta_{3j}^{br} = 0$	0.090 ** (0.04)	0.078 ** (0.04)
Overall Performance	$(w_{li}^{*br}\beta_{3i}^{br} - w_{si}^{*br}\beta_{2i}^{br}) - (w_{lj}^{*br}\beta_{3j}^{br} - w_{sj}^{*br}\beta_{2j}^{br})$ $\text{MPPD}_i^{br} - \text{MPPD}_j^{br}$	0.080 *** (0.02)	0.071 *** (0.02)

Table 10: Comparisons in the trading performances of one trading rule in different market conditions

This table reports comparisons between the trading performances of one trading rule, including the best VMA, best MA, and best MSV rule, in bull markets and that in bear markets. Bull and bear markets are represented by the index bl and br respectively. For the i^{th} rule, the value of β_{2i}^{bl} and β_{2i}^{br} (β_{3i}^{bl} and β_{3i}^{br}) can be explained as the mean profit/loss over its short-position (long-positions) periods in bull and bear markets, while MPPD_i^{bl} and MPPD_i^{br} measure its mean profit per day in these two market conditions. We use the Wald test to implement these comparisons, based on the Newey-West (1987) covariance matrix. In the parentheses are the Newey-West (1987) robust standard errors. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Rule (i)	Position	Comparison	bl = Bull, br = Bear
VMA	Short Position	$\beta_{2i}^{bl} - \beta_{2i}^{br} = 0$	0.221 ***
			(0.04)
	Long Position	$\beta_{3i}^{bl} - \beta_{3i}^{br} = 0$	0.139 ***
			(0.03)
	Overall Performance	$(w_{li}^{*bl}\beta_{3i}^{bl} - w_{si}^{*bl}\beta_{2i}^{bl}) - (w_{li}^{*br}\beta_{3i}^{br} - w_{si}^{*br}\beta_{2i}^{br})$	-0.031 **
		$\text{MPPD}_i^{bl} - \text{MPPD}_i^{br}$	(0.02)
MA	Short Position	$\beta_{2i}^{bl} - \beta_{2i}^{br} = 0$	0.373 ***
			(0.07)
	Long Position	$\beta_{3i}^{bl} - \beta_{3i}^{br} = 0$	0.186 ***
			(0.02)
	Overall Performance	$(w_{li}^{*bl}\beta_{3i}^{bl} - w_{si}^{*bl}\beta_{2i}^{bl}) - (w_{li}^{*br}\beta_{3i}^{br} - w_{si}^{*br}\beta_{2i}^{br})$	0.030 **
			(0.01)
MSV	Short Position	$\beta_{2i}^{bl} - \beta_{2i}^{br} = 0$	0.255 ***
			(0.03)
	Long Position	$\beta_{3i}^{bl} - \beta_{3i}^{br} = 0$	0.187 ***
			(0.02)
	Overall Performance	$(w_{li}^{*bl}\beta_{3i}^{bl} - w_{si}^{*bl}\beta_{2i}^{bl}) - (w_{li}^{*br}\beta_{3i}^{br} - w_{si}^{*br}\beta_{2i}^{br})$	0.022
			(0.02)

2.7 Conclusion

In this paper, we examine whether the information of market volatility is able to improve the profitability of technical analysis. In the previous literature, market volatility acts as a key input in many financial issues. It is, however, not clear whether market volatility has any value in technical analysis. That is, could the information of market volatility enhance the profitability of technical trading rules? If it does, why and how does it work?

We adopt the VMA rule proposed by Chande (1992) as the representative of technical analysis comprising the information of market volatility. Market volatility in the VMA rule is built to detect whether the market price makes big moves in up or down direction or whether it moves in a narrow range. If the market volatility does help the technical trading rules to detect market trend timelier, the VMA rule should be more profitable than other rules.

Using the Superior Predictive Ability test proposed by Hansen (2005), we find that the VMA rule outperforms others with higher profitability. Then we carry out the market timing ability test of Cumby and Modest (1987), and compare the predictive ability for upward and downward trends of the best VMA rule with that of the best MA and best MSV rule. The results that the best VMA rule enjoys better market timing ability may provide evidence to support the value of market volatility in better trend detecting ability.

Finally, we also investigate whether the best VMA rule has differential market timing ability in different market conditions. Empirical results suggest that in bull markets, the best VMA, best MA and best MSV rule do possess predictive ability for future upward trends, but the best VMA rule earns more daily profit than the others. On the other hand, the average loss per day the best VMA rule suffers is less than that of the best MA and best MSV rule in downward trend forecasts. In bear markets, the best VMA rule as well as the best MA and best MSV rule is able to forecast a price decrease well; however, the best VMA rule has less daily loss than the others in the upward trend forecast. As a whole, the best VMA rule outperforms the best MA and best MSV rule both in bull and bear markets.

3 Exploring the Information Content of Market Volatility in Technical Analysis

3.1 Introduction

In last chapter, the information of market volatility improving the profitability of technical analysis is proved. We also explain its better performance possibly stemming from having better timing ability in generating profitable trading signals. Higher profitability and better timing ability display what investors can profit from the information of market volatility considered in forecasting. However, how the market volatility ratio is informationally relevant for the determination of trading signals in technical analysis is still unknown. Thus, the intent of this chapter is to investigate how the information of market volatility affects the generation of trading signals in technical analysis based on the case of the variable moving average (VMA) rule.

The information of market volatility is used to measure whether there is trading opportunity through examining more recent price movements are big or small. The theoretical mechanism of the information of market volatility on affecting the trading signals in the VMA rule appears to be nonlinear and it is usually difficult to empirically capture such nonlinear relationship. However, due to the decision mechanism in the moving average, buying (or selling) when the moving average rises above (or falls below) the current price, using the time-varying-transition-probability (TVTP) Markov switching model can account for their nonlinear relationship.[6] We use a two-state Markov switching model for the gap between the price line and the VMA line in which the transition probabilities of regime-switching is allowed to respond to changes in the information of market volatility. As a result, studying how the information of market volatility influences the regime switching between ”price-above-VMA” and ”price-below-VMA” states is as well as investigating how it affects the generation of trading signals.

Our estimation results indicate that the increase of the change in market volatility will leads to a higher probability of generating signals in the VMA rule. Furthermore, its effect on trading signals is asymmetric across bull and bear markets. The effect that the increase of market

[6]For the detail of the TVTP Markov switching model, see the study of Filardo (1994) and Diebold et al. (1994).

volatility producing higher probability of a selling signal generated is stronger in bear markets than in bull markets. While for a buying signal, its effect in bull markets is larger than in bear markets. These empirical results coincide with the theoretical purpose of the information of market volatility in the VMA rule, taking better advantage of the market price movements.

In this chapter, we also re-explore the value of the information of market volatility for a particular simple MA rule. From the study in last chapter, how the technical trading rule adjusts its time the signal generated to the information of market volatility cannot be revealed directly no matter in the SPA tests or the market timing tests, since the time that the chosen trading rules signal to buy or sell are totally different. It is resulted from the best VMA rule and other trading rules (i.e., the best MA and best MSV rules) we chose to compare are based on the different parameter settings (i.e., the best VMA and best MA rule) or different trading mechanisms (i.e., the best VMA and best MSV rule).

In order to clearly figure out the value of market volatility in technical analysis, we add the information of market volatility to a particular n-day simple MA rule. Through using the Fixed-transition-probability (FTP) and the TVTP Markov-switching models, we compare how the time, the signal generated, changes and how the profit varies after considering the information of market volatility in detecting price movements. For the sake of checking the robustness of the empirical results, six simple MA rules with different settings for period n, 5, 20, 40, 75, 100 and 250, are studied, and we categorize these trading signals into four types according to the time point the trading signals generated between the FTP and the TVTP Markov-switching models. Our results reveal that the same information of market volatility has similar effect on the generation of trading signals for all simple MA rules. We find that the signal time change due to the information of market volatility will benefit investors with higher profit. This result again verifies the information of market volatility is the valuable information in future price movement prediction for technical analysis.

The chapter is organized as follows. Section 2 introduces the moving average trading systems and discusses the theoretical design of market volatility in moving averages. Section 3 presents the TVTP Markov-switching model, describes the data and reports the empirical results in the case the VMA rule. Section 4 contains the estimation results in the TVTP Markov-switching model, data description and the profitability analysis for six simple MA rules. The analysis for four types of trades is also presented. Finally, Section 5 presents conclusions.

3.2 Moving Average Trading Systems

Moving averages are common tools in technical analysis and have been widely used by investment professionals around the world. Moving averages use a smoothing device, averaging asset prices over time, to verify the emergence of new upward or downward price movements. The most widely used moving averages, the Simple Moving Average (SMA), by definition is as follows:

$$\text{SMA}_{n,t} = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i}, \tag{14}$$

where n is the fixed time interval over which the average is calculated and P_{t-i} is the asset price at time $t-i$. In the SMA, each price within the n periods is equally weighted based on the assumption that old prices are equally as relevant as more recent ones when they are used to forecast future price movement.

The mechanism of moving average systems to detect price movements stems from its characteristic, lagging behind the current price. In a rising market in which the direction of price movement is positive, the moving average will below the rising price line, whereas it will be above the falling price line when the price direction is negative. Therefore, when the current price crosses the moving average from below, it implies that the price direction reverses from downward to upward. In this situation, the best strategy, buying the asset (the long positions), will be recommended. On the contrary, when the current price crosses the moving average from above, sell signals (the short positions) will be generated because the market might be falling in the future. Similarly, the long-period moving average lags the short-period moving average. Thus, when the short-period moving average breaks above (below) the long-period moving average, a upward (downward) price movement is considered to be initiated.

The size of n determines the price movements detected are short-term or long-term. A SMA with smaller n is used to forecast short-term price movements and is called the shorter-period SMA rule. Due to the crossover trading mechanism, a shorter-period SMA rule tends to follow changes in underlying asset prices more closely and then generates trading signals quickly since it gives more recent prices higher weight in the average. In other words, as n is smaller, the weight of more recent prices in forming moving averages is greater and consequently the probability of the SMA rule to generate signals is higher.

3.2.1 Market Volatility in Moving Averages

Proposed by Chande (1992), the Variable Moving Average (VMA) rule is the moving average comprising the information of market volatility. It is built to motivate the SMA rule to be more responsive to the ever-changing market conditions on the premise that the SMA rule's equally weighting to each price within the fixed n periods to detect future price movements is not suitable for all market conditions. For example, if the market price moves directionally (trending market), more recent prices are relatively important in moving averages to take better advantage of the price movements. In this situation, a SMA rule with smaller n (shorter-period or fast SMA) will be a better choice to get early signals. Conversely, if the price changes become directionless and noisier (ranging market), the best investment strategy is not to buy and sell any assets. Therefore, applying a SMA rule with larger n (longer-period or slow SMA) will avoid the usual whipsaw effect of over trading since the probability of generating trading signals is reduced by not giving more recent prices higher weight in moving averages. Compared to the SMA rule's equally weighting, the central idea of the VMA rule is that in detecting future price movements, the relative importance between old prices and more recent ones in moving averages should not be equal; rather, it should depend on the market condition.

The VMA rule seeks to identify and adapt to ever-changing market conditions by use of the market volatility ratio (VR) as follows:

$$\text{VR}_t \equiv \frac{\sigma_t^n}{\sigma_t^{ref}}, \tag{15}$$

where σ_t^n is the standard deviation of closing prices over past n periods at time t, while σ_t^{ref} is the reference standard deviation of closing prices over some period of time longer than n at time t. In essence the market volatility ratio measures the relative amplitude of price movements between the past n periods and the reference period. The limiting values of the market volatility ratio are $\mathrm{VR}_t > 0$. If the market price makes big moves in up or down direction, a reflection of recent good news or bad news, we expect that recent market prices will be more volatile than the reference period. Therefore, $\mathrm{VR}_t > 1$ may imply that the present market is trending. Conversely, if the market price over the past n periods moves in a narrower range due to no influential or new information appearing on the market, $\mathrm{VR}_t < 1$, i.e. the ranging market. To sum up, the size of VR_t makes the judgement that whether the present market is active or not.

In order to adjust weighting that past prices have in moving averages according to market conditions, the VMA rule is constructed by revising the Exponential Moving Averages as follows:

$$\mathrm{VMA}_t = \alpha_t^* P_t + (1 - \alpha_t^*)\mathrm{VMA}_{t-1}, \tag{16}$$

$$\alpha_t^* = \alpha \mathrm{VR}_t, \tag{17}$$

$$N_t^* = \frac{2}{\alpha_t^*} - 1. \tag{18}$$

where VMA_t is the current value of the Variable Moving Average; VMA_{t-1} is the value of the Variable Moving Average in previous period; α_t^* is the scaled smoothing parameter at time t, consists of a constant term α and the market volatility ratio, VR_t; P_t is the closing price at time t; N_t^* is the effective length of past prices used to calculate the moving average value at time t.[7] Except for that fact that the smoothing parameter and effective length are time variable, the VMA_t in Eq. (16) is mathematically identical to the conventional Exponential Moving Averages model.[8]

In the VMA, VR_t acts as the automatically adjusting device for choosing more suitable effective length in constructing the moving average. As the market is trending, VR_t will be

[7]Hutson (1984) shows that the relationship between N^* and α^* in Eq. (18) can be used to approximate the value of the exponential smoothing constant for an equivalent N^*-period SMA.

[8]As $\mathrm{VR}_t = 1$ for all t, the VMA will become the Exponential Moving Averages.

larger than one. Therefore, the VMA will place more weight (larger α_t^*) on the most recent price and adopt a shorter length of past prices (smaller N_t^*). As a result, the probability to take better advantage of the price movements will be increased since the gap between the VMA and the current price will be narrower. In contrast, as the market is ranging, VR_t will be smaller than one. A greater weight is no longer given to the more recent data (smaller α_t^*) and a longer length of past prices is consider (larger N_t^*). Consequently, the possibility to suffer losses from false tradings can be reduced. In summary, the information of market volatility makes the VMA to be a more responsive indicator to automatically become a shorter-period SMA or change into a longer-period one based on the whether the market is trending or ranging.

3.3 Trading Signals and Market Volatility Ratio

Since we have introduced that the market volatility ratio has the theoretical advantage of improving the SMA rule to be a smarter indicator by automatically adjusting its effective length, we now empirically examine how the market volatility ratio works in the signal generating process of moving averages by real trading data. The real trading data is created by applying the 2,020 VMA rules to the Dow Jones Industrial Average (DJIA) daily closing price from Oct 1, 1928 to June 28, 2010 and choosing the best VMA rule, enjoying the largest excess return during this period, as our research target to explore how the market volatility ratio is informationally relevant for the determination of signals in moving averages.[9]

In order to address the above question, we use a modified version of the Markov-switching model in the study of Filardo (1994), the time-varying-transition-probability (TVTP) Markov-switching model. Similar to the SMA rule, the VMA rule uses the moving average crossovers to generate trading signals, that is, a buying (selling) signal occurs when the current price crosses above (below) the VMA. In other words, if the value, the current price minus the VMA, changes from negative to positive, a buying signal is generated. If it differs from positive to negative,

[9]The 2,020 VMA rules are made up of many different parameter values for α, n of σ_t^n and ref of σ_t^{ref}, which come from the settings in Chande (1992) and Chande and Kroll (1994) and the suggestions from the websites of professional trading companies. Among the universe of 2,020 VMA rules, the best one is as follows: $\alpha = 0.049 (N = 40)$, $n = 15$, $ref = 30$, $band = 0.0005$.

we will get a selling signal. Therefore, we can define a new variable, the price value minus the VMA value at each time, and use a simple two-state mean Markov-switching model of this new variable (positive and negative mean) to describe the signal generating process of the VMA rule. It is, foremost, the time-varying-transition-probability in the Markov-switching model allows us to explore how the market volatility ratio affects the dynamics of switching in states because the probability of switching between states can be designed to depend on the market volatility ratio.

3.3.1 The TVTP Markov-Switching Model

Let $d_t = p_t - \text{vma}_t$, where p_t and vma_t are the logarithm of the DJIA closing price and the VMA value at time t, respectively.[10] In other words, d_t measures the gap between the logarithm of the price line and that of the VMA line. Consider a two-state Markov-switching model of d_t:

$$d_t = \mu_{S_t} + \sum_{j=1}^{k} \beta_{S_t,j} d_{t-j} + \epsilon_t, \quad \epsilon_t \sim i.i.d.N(0, \sigma^2_{S_t}). \tag{19}$$

where term μ_{S_t} and $\sigma^2_{S_t}$ are respectively the state-dependent mean and variance of d_t. d_{t-j} is allowed to have different impacts on d_t across different states, $\beta_{S_t,j}$. The unobserved state variable S_t is a latent dummy variable equaling either 0 or 1, which indicates that the price line is above/below the VMA line, i.e. μ_{S_t} is either positive or negative. It is assumed to follow a two-state Markov process with time-varying transition probability matrix:

$$P(t) = \begin{bmatrix} p_t^{00}(z_t) & p_t^{01}(z_t) \\ p_t^{10}(z_t) & p_t^{11}(z_t) \end{bmatrix} = \begin{bmatrix} p_t^{00}(z_t) & 1 - p_t^{00}(z_t) \\ 1 - p_t^{11}(z_t) & p_t^{11}(z_t) \end{bmatrix}, \tag{20}$$

where $p_t^{ij}(z_t) = P(s_t = j | s_{t-1} = i, z_t)$ and z_t consists of the information of market volatility. Therefore, it is obvious that the time-varying transition probability matrix in Eq. (20) displays how the two different regimes shift over time. p_t^{01} and p_t^{10} measure the probability of a switch from State 0 to State 1 and from State 1 to State 0 at time t. As d_t switches from State 0

[10] The trading signals generated by the price value and the VMA value are the same as that generated by their logarithms.

($\mu_{S_t} > 0$) to State 1 ($\mu_{S_t} < 0$), it implies that there will be a selling signal because the price line crosses the VMA line from above. On the contrary, a buying signal will be expected as d_t changes from State 1 to State 0, due to the price line crossing the VMA line from below. In this study, the probability of regime switching is assumed to vary with the evolution of the information of market volatility. In other words, the information of the market volatility will affect the signal generation of the VMA rule.

The functions of the transition probabilities are then specified as follows:

$$p_t^{01}(z_t) = \frac{\exp\{\theta_0 + z_t'\theta\}}{1 + \exp\{\theta_0 + z_t'\theta\}}, \tag{21}$$

$$p_t^{10}(z_t) = \frac{\exp\{\gamma_0 + z_t'\gamma\}}{1 + \exp\{\gamma_0 + z_t'\gamma\}}. \tag{22}$$

Here, z_t is a $q \times 1$ vector of variables, $(z_{1t}, z_{2t}, \ldots, z_{qt})'$, while θ and γ are $q \times 1$ vectors of coefficients, $(\theta_1, \theta_2, \ldots, \theta_q)'$ and $(\gamma_1, \gamma_2, \ldots, \gamma_q)'$. And clearly,

$$\frac{\partial p_t^{01}}{\partial z_{it}} = \theta_i\, p_t^{01}(1 - p_t^{01}),\ i = 1, ..., q, \tag{23}$$

$$\frac{\partial p_t^{10}}{\partial z_{it}} = \gamma_i\, p_t^{10}(1 - p_t^{10}),\ i = 1, ..., q. \tag{24}$$

Since $0 \leq p_t^{01}, p_t^{10} \leq 1$, the signs of $\partial p_t^{01}/\partial z_{it}$ and $\partial p_t^{10}/\partial z_{it}$ are determined by the signs of θ_i and γ_i, respectively. Therefore, the estimates of θ_i and γ_i show how the information of market volatility influences the probability of the generation of trading signals in the VMA rule.

In this study, we adopt VR_{t-1}, dVR_t and dVR_{t-1} as the candidate for z_t. VR_{t-1} is the market volatility ratio at time t-1, while dVR_t is defined as VR_t minus VR_{t-1} in order to measure whether the market volatility ratio is increasing from time t-1 to time t. According to the definition of VR_t, $\sigma_t^n/\sigma_t^{ref}$ with $ref > n$, the increase of the market volatility ratio from time t-1 to time t (i.e., $\text{dVR}_t > 0$) can imply $\sigma_t^n > \sigma_{t-1}^n$ based on the premise that $\sigma_t^{ref} \simeq \sigma_{t-1}^{ref}$ as the reference period is longer enough. Here, $\sigma_t^n > \sigma_{t-1}^n$ denotes that the price variation in the period from time t-1 to time t is larger than that from time t-n to time t-n+1. We explain the market experiencing a larger price movement within the period from time t-1 to time t is due to there might be an influential or new information surged in this period. On the contrary, $\text{dVR}_t < 0$ illustrates the situation that the price variation from time t-1 to time t is less, compared with that from time t-n to time t-n+1. Less variation in price from time t-1 to time t may denote that the information in this period is relatively less influential than that the period from time t-n to time t-n+1. Similarly dVR_{t-1}, defined as VR_{t-1} minus VR_{t-2}, measures whether there exists a larger or smaller change in price from t-2 to time t-1. As a result, dVR_t and dVR_{t-1} are used to see whether there are any new information or influential shock appearing from time t-2 in the market.

3.3.2 Data

d_t examined in this paper comes from the difference between the DJIA daily index and the value of the best VMA rule applied in the period of 1928/10/1 to 2010/6/28. Since the best VMA rule needs 30 days to generate trading signals, we have 20,496 observations for d_t from 1928/11/14 to 2010/6/28. This paper focuses on the U.S. stock market and investigates the role of market volatility ratio in the generation of signals in moving averages both in full sample and sub-samples. The reason to conduct sub-sample analysis is to serve as the robustness check of our empirical results.

We split the full sample into the following three sub-samples: 1928/11/14−1938/12/30, 1939/01/01−1987/10/18 and 1987/10/19−2010/06/28. These sub-samples are chosen for two common reasons. The first sub-sample includes the turbulent times of the 1930s great depression. The second and the last sub-samples are divided based on the most important economic event (change in price in percentage terms) to recently affect the DJIA index, the October crash of 1987. Thus, the second one comprises the World War II and the pre-October 1987 crash periods, and the last one covers the post-October 1987 crash period.

Table 11 reports the summary statistics and the unit root tests results for d_t, VR_{t-1} and dVR_t both for the full and sub-samples. We observe that the d_t distribution exhibits left skewness and excess kurtosis for the full and all sub-samples. Both VR_{t-1} and dVR_t have a long right tail in the sample distributions; however, the VR_{t-1} distribution is platykurtic but dVR_t's is leptokurtic. For these three variables, we also conduct unit root tests to investigate whether these series are stationary. The results of the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test show that the hypothesis of unit root process is rejected for each series in the full and all sub-sample periods.[11]

3.3.3 Empirical Results

Table 12 reports the estimation results for two types of the Markov-Switching model, the fixed-transition-probability (FTP) MS model and the TVTP MS model. First of all, it is obvious that the FTP MS model with AR lag 1 in d_t yields a quite higher value of the likelihood function than that with no AR lags; therefore, AR lag 1 in d_t is chosen in Eq. (19).

The FTP MS-AR(1) model, where the process is allowed to switch between regimes, identifies two regimes. The Regime 0, with a positive mean ($\widehat{\mu}_0 > 0$), represents the situation that the VMA line is below the rising price line. While the Regime 1 stands for the opposite case that the VMA line is above the falling price due to its negative mean ($\widehat{\mu}_1 < 0$). The estimated AR1 coefficients, $\widehat{\beta}_{0,1}$ and $\widehat{\beta}_{1,1}$, indicate that d_t in both regimes is quite persistent. The higher variance in d_t in Regime 1 displays that the VMA line can not trace the price line more closely in the case that the price descends.

We label the positive-mean stable and negative-mean volatile states in d_t as the rising markets with the upward direction of price movements, and falling markets with the downward price direction, respectively. As d_t switches from a rising-market state to a falling-market state, a selling signal will be suggested by the VMA rule. Conversely, as the regime shifts from a falling-market to a rising-market, the VMA rule will generate a buying signals. Finally, the transition probabilities in the FTP MS-AR(1) model exhibits that both rising-market and falling-market states are highly persistent. The rising-market regime (Regime 0) persists on average for $1/(1 - \widehat{p}^{00}) = 111$ days while it is expected that the falling-market regime (Regime 1) will

[11] We conduct two types of test equations in the ADF and PP test. One includes the intercept term in the test equations. The other contains the intercept and trend terms in the models. The results in these two types of test models are the same. Thus, we just report results of the unit root tests in which the intercept term is included in the models.

Table 11: Descriptive Statistics And Unit Root Tests

This table reports summary statistics and the unit root tests results for d_t, VR_{t-1} and dVR_t in the full and sub-sample periods. d_t is defined as p_t minus vma_t, where p_t and vma_t are the logarithm of the DJIA closing price and the VMA value at time t. VR_{t-1} is the market volatility ratio at time t-1 and dVR_t is described as VR_t minus VR_{t-1}. The values of vma_t, VR_{t-1} and dVR_t come from applying the best VMA rule in the DJIA daily index. The full sample period is between Nov 14, 1928 and June 28, 2010, with 20,496 observations. Our three sub-samples are built in order to distinguish the 1930s great depression period, pre-October 1987 crash periods, and post-October 1987 crash periods. They are 1928/11/14−1938/12/30, 1939/01/01−1987/10/18 and 1987/10/19−2010/06/28 with 2,528, 12,246 and 5,722 observations, respectively. For unit root tests, ADF and PP are augmented Dickey-Fuller and Phillips-Perron test statistics. In both tests, the test equation includes the intercept term and the null hypothesis is that the series has a unit root. Test critical values for ADF and PP are -3.443834 (1%), -2.867379 (5%), and -2.569943 (10%). Lags in ADF tests are chosen by Schwartz Bayesian information criterion (SC).

	d_t				VR_{t-1}				dVR_t			
	Full	Sub. 1	Sub. 2	Sub. 3	Full	Sub. 1	Sub. 2	Sub. 3	Full	Sub. 1	Sub. 2	Sub. 3
Descriptive Statistics												
Mean	0.005	-0.010	0.007	0.007	0.739	0.729	0.735	0.752	0.00001	0.00010	0.00004	-0.00008
Max	0.275	0.275	0.127	0.098	1.383	1.352	1.383	1.380	0.450	0.379	0.450	0.417
Min	-0.407	-0.407	-0.207	-0.347	0.081	0.128	0.081	0.156	-0.559	-0.325	-0.559	-0.368
Standard Deviation	0.046	0.090	0.034	0.038	0.269	0.255	0.274	0.263	0.074	0.072	0.075	0.074
Skewness	-1.434	-0.657	-0.676	-1.757	0.137	0.192	0.135	0.125	0.183	0.185	0.206	0.132
Kurtosis	11.554	4.626	4.887	9.818	2.164	2.219	2.113	2.249	4.772	4.638	4.766	4.830
Unit root tests												
ADF	-17.015	-5.793	-13.743	-10.728	-36.072	-12.679	-28.146	-18.564	-36.607	-17.632	-33.374	-23.200
PP	-17.550	-5.539	-13.301	-12.954	-8.629	-12.278	-8.640	-10.666	-97.568	-18.397	-47.320	-29.272

persist for $1/(1-\widehat{p}^{11}) = 26$ days. In other words, the long positions suggested by the VMA rule will keep for 111.11 days on average. But the short positions will keep for a shorter period, 26.32 days.

The last column in Table 12 presents the results for the TVTP MS model. The elements in z_t, dVR_t and dVR_{t-1}, are chosen according to the suggestions by both Akaike's information criterion (AIC) and Schwarz's criterion (SC).[12] Using dVR_t and dVR_{t-1} enables us to see how the dynamic of the VR_t affecting the generation of the VMA's trading signals. The generation of crossovers between the price line and the VMA line is mainly due to two conditions, based on an important premise that the direction of the price line and the VMA line before a trading signals generated should be opposite. The first condition is whether the value of the VR_t is large enough to make the VMA line approaching the price line. The second one is the difference between the P_{t-1} and VMA_{t-1}. If the VMA line is near to the price line at time t-1 due to the big VR_{t-1}, a trading signal might be generated at time t even the value of VR_t is not very large. In this study, dVR_t and dVR_{t-1} can be used to measure the conditions of the crossovers. If the dVR_t is increasing, we expect that it might result from a higher value of VR_t. While the increase in the dVR_{t-1} might be explained as due to a increase in VR_{t-1}. Higher VR_{t-1} will make the difference between the price line and the VMA line become narrower.

In the TVTP MS model, the estimation results in d_t equation (i.e., Eq. (19)) is similar to those in the FTP MS-AR(1) model. We still have a clear identification of the rising-market and the falling-market states. Since the Regime 0 and 1 represent the rising-market and the falling-market states respectively, the estimates of θ_i and γ_i for $i = 1, 2$ measure how the information of market volatility affects the generation of a selling signal and a buying signal for the VMA rule, respectively. At the 5% significant level, it is found that $\widehat{\theta}_1 > 0$, $\widehat{\theta}_2 < 0$, $\widehat{\gamma}_2 > 0$ but $\widehat{\gamma}_1$ is not significantly different from zero. Here, $\widehat{\gamma}_2 > 0$ means that the increase of dVR_{t-1} raises the probability of generating a buying signal at time t. The insignificance of $\widehat{\gamma}_1$ denotes that no matter how the price fluctuates from time t-1 to time t, the generation of a buying signal will not

[12] We have tried different kinds of z_t such as dVR_t, VR_{t-1}, dVR_{t-1}, $(\mathrm{dVR}_t, \mathrm{dVR}_{t-1})$ and $(\mathrm{dVR}_t, \mathrm{VR}_{t-1})$ and found that $(\mathrm{dVR}_t, \mathrm{dVR}_{t-1})$ was the best one.

be affected. dVR_t and dVR_{t-1} have different effect on the probability of generating a selling signal. The increase of dVR_t or the decrease of dVR_{t-1} makes the probability of generating a selling signal higher, because we get $\widehat{\theta}_1 > 0$ and $\widehat{\theta}_2 < 0$.

We can further investigate the economic significance of the effect of the change of the market volatility ratio on the transition probability from one regime to another. They are calculated by $\partial p_t^{01}/\partial z_{it} = \widehat{\theta}_i\, \widehat{p}_t^{01}[1 - \widehat{p}_t^{01}]$ and $\partial p_t^{10}/\partial z_{it} = \widehat{\gamma}_i\, \widehat{p}_t^{10}[1 - \widehat{p}_t^{10}]$, where $\widehat{p}_t^{01} = p_t^{01}(\widehat{\theta_0}, \widehat{\theta_1}, \widehat{\theta_2}, \overline{z}_{it})$, $\widehat{p}_t^{10} = p_t^{10}(\widehat{\gamma_0}, \widehat{\gamma_1}, \widehat{\gamma_2}, \overline{z}_{it})$ and $\overline{z}_{it} = (\overline{\mathrm{dVR}}_t, \overline{\mathrm{dVR}}_{t-1})$.[13] $\overline{\mathrm{dVR}}_t$ and $\overline{\mathrm{dVR}}_{t-1}$ are the mean of dVR_t and dVR_{t-1}, respectively. Every 0.1 increase in dVR_t increase the probability of generating a selling signal with $\Delta p_t^{01} = 0.728$ but it will not affect the probability of generating a buying signal. However, an 0.1 increase in dVR_{t-1} reduces the probability of a selling signal with $\Delta p_t^{01} = -0.349$ but it enlarges the probability of a buying signal with $\Delta p_t^{10} = 0.268$.

The reason why we get $\widehat{\gamma}_1 = 0$ is probably because that some cases in the sample show that dVR_t has positive effect on the probability of a long position signaled at time t, whereas others display that it has negative effect. The two types of cases make $\widehat{\gamma}_1$ insignificant. In the cases of negative effect, the increases in dVR_{t-1} dominates that in dVR_t, since VR_t from t-2 to time t-1 increases a lot to force the value of the VMA_{t-1} to near to the value of the P_{t-1}. Therefore, the possibility that the best VMA rule generates a buying signal at time t is higher no matter how big the variation of the market price was from time t-1 to time t, even the value of VR_t is less than that of VR_{t-1}. According to the results in the economic significance of the effect of dVR_t and dVR_{t-1}, the probability of a buying signal will be raised by 0.537 and 0.805 ($\Delta p_t^{10} = 0.537, 0.805$) as dVR_{t-1} increases by 0.2 and 0.3 unit, respectively. Once dVR_{t-1} increases by 0.3 unit, it means that there is a quite big variation in price from time t-2 to time t-1 (i.e., the value of VR_{t-1} is quite larger than that of VR_{t-2}). In the cases of positive effect, the crossovers are determined by both the increase of dVR_t and dVR_{t-1}. Here, the strength of the increase in dVR_{t-1} is less, compared to that in the cases of negative effect.

Moreover, if we set the significant level as 10%, $\widehat{\gamma}_1 < 0$ and every 0.1 increase in dVR_t

[13] The details of $\widehat{p}_t^{01}$ and $\widehat{p}_t^{10}$ are as follows:
$\widehat{p}_t^{01} = \exp\{\widehat{\theta}_0 + \widehat{\theta}_1\, \overline{\mathrm{dVR}}_t + \widehat{\theta}_2\, \overline{\mathrm{dVR}}_{t-1}\}/1 + \exp\{\widehat{\theta}_0 + \widehat{\theta}_1\, \overline{\mathrm{dVR}}_t + \widehat{\theta}_2\, \overline{\mathrm{dVR}}_{t-1}\}$,
$\widehat{p}_t^{10} = \exp\{\widehat{\gamma}_0 + \widehat{\gamma}_1\, \overline{\mathrm{dVR}}_t + \widehat{\gamma}_2\, \overline{\mathrm{dVR}}_{t-1}\}/1 + \exp\{\widehat{\gamma}_0 + \widehat{\gamma}_1\, \overline{\mathrm{dVR}}_t + \widehat{\gamma}_2\, \overline{\mathrm{dVR}}_{t-1}\}$.

will make the probability to signal buying the asset at time t lower by 0.032 ($\Delta p_t^{10} = -0.032$). However, this effect is relatively little. Finally, $\widehat{\gamma}_1 < 0$ and $\widehat{\gamma}_2 > 0$ illustrate that the cases of negative effect has higher frequency in the sample. On average, the main factor causing the VMA rule to signal a long position at time t is that the market price varies a lot from time t-2 to time t-1, since there might be an important information in the market at time t-1.

For the selling signals, $\widehat{\theta}_1 > 0$, $\widehat{\theta}_2 < 0$ and their results in economic significance show that the main factor affecting the generation of the selling signals is dVR_t. The strong effect of a 0.1 increase in dVR_t on the possibility of a selling signal generated at time t and $\widehat{\theta}_2 < 0$ implies that the value of VR_{t-1} and VR_{t-2} are not small. If the value of VR_{t-2} is large and dVR_{t-1} increases, it makes senses that the probability of a selling signal at time t will be reduced (i.e., $\widehat{\theta}_2 < 0$), since in this case time t-1 will be considered to be a better time to have a short position. Furthermore, $\widehat{\theta}_1 > 0$ with stronger effect and $\widehat{\theta}_2 < 0$ can be used to measure how the market price behaves before a selling signal, high VR_{t-2} and the decrease of dVR_{t-1} (i.e., the difference between VR_{t-2} and VR_{t-1} is less). Before time t-2, the recent market price is more volatile than the reference period due to a reflection of recent information (i.e., high VR_{t-2}), and the variation in market price becomes moderate from time t-2 to time t-1 causing the decrease of dVR_{t-1}. However, a negative shock surged at time t-1 in the market and the downward price jump will take place making the increase of dVR_t. As a result, the probability of a selling signal will be increased in order to take advantage of the downward price movement.

In summary, we use dVR_{t-1} and dVR_t to detect whether there is any influential information or new shock in the market, based on the premise that the variation in market prices is due to the reaction to the information in the market. Once the information emerged in the market is more influential, the VMA rule will response to it to make the change in dVR_{t-1} or dVR_t. Therefore, it will raise the probability of taking better advantage of the price movement.

3.3.4 Robustness

In order to check the robustness of the empirical results, the following modifications are made. First, we consider different sample periods. Second, we examine the effect of dVR_{t-1} and dVR_t

Table 12: Markov-Switching Models: Full Sample

This table presents the estimation results of two types of the Markov-Switching model, the Fixed-Transition-Probability (FTP) and the Time-Varying-Transition-Probability (TVTP) MS model, for the full sample. The MS-AR(0) model is $d_t = \mu_{S_t} + \epsilon_t$ with mean/variance (μ_0, σ_0^2) in regime 0 and (μ_1, σ_1^2) in regime 1. While the MS-AR(1) model is $d_t = \mu_{S_t} + \beta_{S_t,1} d_{t-1} + \epsilon_t$ with $(\mu_0, \sigma_0^2, \beta_{0,1})$ in regime 0 and $(\mu_1, \sigma_1^2, \beta_{1,1})$ in regime 1. $\beta_{S_t,1}$ is the AR1 coefficient in each regime. The mean equation in the TVTP MS model is based on the AR(1) model and we specify the time-varying transition probabilities as $p_t^{01}(z_t) = \exp\{\theta_0 + z_t'\theta\}/1 + \exp\{\theta_0 + z_t'\theta\}$ and $p_t^{10}(z_t) = \exp\{\gamma_0 + z_t'\gamma\}/1 + \exp\{\gamma_0 + z_t'\gamma\}$, where z_t represents the information of market volatility and is a 2×1 vector of variables, $z_t = (\text{dVR}_t, \text{dVR}_{t-1})$. θ and γ are 2×1 vectors of coefficients, $(\theta_1, \theta_2)'$ and $(\gamma_1, \gamma_2)'$. The entries in brackets are the standard errors. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level. LogLik represents the value of log-likelihood function.

	Fixed-Transition-Probability		Time-Varying-Transition-Probability
	MS-AR(0)	MS-AR(1)	MS-AR(1) with $z_t = (\text{dVR}_t, \text{dVR}_{t-1})$
μ_0	0.021 ***	0.0005 ***	0.0005 ***
	(0.0003)	(0.0001)	(0.0001)
μ_1	-0.026 ***	-0.0014 ***	-0.0013 ***
	(0.0010)	(0.0004)	(0.0004)
$\beta_{0,1}$		0.968 ***	0.965 ***
		(0.0020)	(0.0019)
$\beta_{1,1}$		0.962 ***	0.963 ***
		(0.0044)	(0.0044)
σ_0	0.019 ***	0.007 ***	-0.007 ***
	(0.0002)	(0.0001)	(0.0001)
σ_1	0.063 ***	0.021 ***	0.022 ***
	(0.0007)	(0.0003)	(0.0003)
p^{00}	0.984 ***	0.991 ***	
	(0.0012)	(0.0010)	
p^{11}	0.970 ***	0.962 ***	
	(0.0022)	(0.0042)	
θ_0			-1.105 ***
			(0.19)
γ_0			1.568 ***
			(0.15)
θ_1			38.970 ***
			(1.89)
γ_1			-2.242 *
			(1.34)
θ_2			-18.670 ***
			(1.47)
γ_2			18.810 ***
			(1.67)
LogLik	42877.7	67910.1	68141.5

under different market conditions.

Results in sub-samples The results for three sub-samples are reported in Table 13. At the 5% significant level, the result that $\widehat{\theta}_1 > 0$ and $\widehat{\theta}_2 < 0$ holds for all sub-samples. $\widehat{\gamma}_1 = 0$ and $\widehat{\gamma}_2 > 0$ are also found, expect that $\widehat{\gamma}_1$ is negative in the second sub-sample. It is found that the effect of dVR_t on the probability of a buying signal is still relatively slight. Its 0.1 increase will just make the probability of a long position lower by 0.059 ($\Delta p_t^{10} = -0.059$). To sum up, the evidence indicates that previous conclusion in the results of full sample stands, which suggests that the main empirical results are robust.

Results in bull and bear markets In addition to checking the robustness of our results, this section investigates a further question: Does the information of market volatility have the same sort of effects on the probability of generating trading signals in different market conditions? In order to address this question, we modify the function of the transition probability of the TVTP MS model as follows:

$$p_t^{01}(z_t) = \frac{\exp\{\theta_0 + \theta_1^{bl}\mathrm{dVR}_t^{bl} + \theta_1^{br}\mathrm{dVR}_t^{br} + \theta_2^{bl}\mathrm{dVR}_{t-1}^{bl} + \theta_2^{br}\mathrm{dVR}_{t-1}^{br}\}}{1+\exp\{\theta_0 + \theta_1^{bl}\mathrm{dVR}_t^{bl} + \theta_1^{br}\mathrm{dVR}_t^{br} + \theta_2^{bl}\mathrm{dVR}_{t-1}^{bl} + \theta_2^{br}\mathrm{dVR}_{t-1}^{br}\}}, \tag{25}$$

$$p_t^{10}(z_t) = \frac{\exp\{\gamma_0 + \gamma_1^{bl}\mathrm{dVR}_t^{bl} + \gamma_1^{br}\mathrm{dVR}_t^{br} + \gamma_2^{bl}\mathrm{dVR}_{t-1}^{bl} + \gamma_2^{br}\mathrm{dVR}_{t-1}^{br}\}}{1+\exp\{\gamma_0 + \gamma_1^{bl}\mathrm{dVR}_t^{bl} + \gamma_1^{br}\mathrm{dVR}_t^{br} + \gamma_2^{bl}\mathrm{dVR}_{t-1}^{bl} + \gamma_2^{br}\mathrm{dVR}_{t-1}^{br}\}}. \tag{26}$$

where,

$$\mathrm{dVR}_t^{bl} = \mathrm{dVR}_t \times \mathrm{Bull}_t, \tag{27}$$

$$\mathrm{dVR}_t^{br} = \mathrm{dVR}_t \times (1 - \mathrm{Bull}_t), \tag{28}$$

$$\mathrm{Bull}_t = \begin{cases} 1 & \text{if it is the bull market at time } t, \\ 0 & \text{bear market.} \end{cases} \tag{29}$$

Here, we still use the widely reported characteristics of the stock market in the literature, bull and bear markets to stand for different market conditions in the stock market. The binary variable, Bull_t, is constructed from the dating algorithm proposed by Pagan and Sossounov (2003).

Table 13: Robustness Check: Sub-samples

This table reports the estimation results of TVTP Markov-Switching model for the three sub-samples. These sub-samples are resulted from splitting the full sample by two important economic events. The model is $d_t = \mu_{S_t} + \beta_{S_t,1} d_{t-1} + \epsilon_t$ with mean/variance/AR1 coefficient $(\mu_0, \sigma_0^2, \beta_{0,1})$ in regime 0 and $(\mu_1, \sigma_1^2, \beta_{1,1})$ in regime 1. The time-varying transition probabilities are specified as $p_t^{01}(z_t) = \exp\{\theta_0 + z_t'\theta\}/1 + \exp\{\theta_0 + z_t'\theta\}$ and $p_t^{10}(z_t) = \exp\{\gamma_0 + z_t'\gamma\}/1 + \exp\{\gamma_0 + z_t'\gamma\}$, where z_t represents the information of market volatility and is a 2×1 vector of variables, $z_t = (\mathrm{dVR}_t, \mathrm{dVR}_{t-1})$. θ and γ are 2×1 vectors of coefficients, $(\theta_1, \theta_2)'$ and $(\gamma_1, \gamma_2)'$. The entries in brackets are the standard errors. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

	Sub-sample 1	Sub-sample 2	Sub-sample 3
	1928/11/14−1938/12/30	1939/01/01−1987/10/18	1987/10/19−2010/06/28
μ_0	0.002 ***	0.001 ***	0.001 ***
	(0.0004)	(0.0001)	(0.0001)
μ_1	-0.002 **	-0.001 **	-0.002 ***
	(0.0009)	(0.0002)	(0.0006)
$\beta_{0,1}$	0.936 ***	0.964 ***	0.947 ***
	(0.0082)	(0.0026)	(0.0049)
$\beta_{1,1}$	0.971 ***	0.975 ***	0.927 ***
	(0.0074)	(0.0049)	(0.0103)
σ_0	-0.010 ***	-0.005 ***	-0.007 ***
	(0.0003)	(0.0001)	(0.0001)
σ_1	0.029 ***	0.012 ***	-0.018 ***
	(0.0008)	(0.0003)	(0.0005)
θ_0	-1.226	-0.211	-2.413 ***
	(0.80)	(0.28)	(0.88)
γ_0	0.636	2.224 ***	1.379 ***
	(0.41)	(0.17)	(0.32)
θ_1	49.360 ***	46.460 ***	51.840 ***
	(9.39)	(3.44)	(7.34)
γ_1	-8.858	-6.704 ***	1.036
	(6.47)	(1.78)	(0.90)
θ_2	-20.160 ***	-24.790 ***	-20.390 ***
	(7.22)	(2.50)	(3.71)
γ_2	26.350 ***	19.780 ***	16.300 ***
	(5.12)	(1.85)	(2.32)

Table 14: Robustness Check: Bull and Bear Markets

This table reports the estimation results of TVTP Markov-Switching model considering different market conditions, bull and bear markets, for the full sample. The model is $d_t = \mu_{S_t} + \beta_{S_t,1} d_{t-1} + \epsilon_t$ with mean/variance/AR1 coefficient $(\mu_0, \sigma_0^2, \beta_{0,1})$ in regime 0 and $(\mu_1, \sigma_1^2, \beta_{1,1})$ in regime 1. The time-varying transition probabilities are specified as $p_t^{01}(z_t) = \exp\{\theta_0 + z_t'\theta\}/1 + \exp\{\theta_0 + z_t'\theta\}$ and $p_t^{10}(z_t) = \exp\{\gamma_0 + z_t'\gamma\}/1 + \exp\{\gamma_0 + z_t'\gamma\}$, where z_t, a 4×1 vector of variables, represents the information of market volatility in the bull and bear market as $z_t = (\text{dVR}_t^{bl}, \text{dVR}_t^{br}, \text{dVR}_{t-1}^{bl}, \text{dVR}_{t-1}^{br})$. The index *bl* and *br* symbolize the bull and bear market, respectively. θ and γ are 4×1 vectors of coefficients, $(\theta_1^{bl}, \theta_1^{br}\theta_2^{bl}, \theta_2^{br})'$ and $(\gamma_1^{bl}, \gamma_1^{br}, \gamma_2^{bl}, \gamma_2^{br})'$. The entries in brackets are the standard errors. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level. LogLik represents the value of log-likelihood function.

	$z_t = (\text{dVR}_t, \text{dVR}_{t-1})$	
μ_0	0.001 *** (0.0001)	
μ_1	-0.001 *** (0.0004)	
$\beta_{0,1}$	0.965 *** (0.0019)	
$\beta_{1,1}$	0.963 *** (0.0045)	
σ_0	0.007 *** (0.0001)	
σ_1	0.022 *** (0.0003)	
θ_0	-1.109 *** (0.4100)	
γ_0	1.601 *** (0.2000)	
Market	Bull $(i = bl)$	Bear $(i = br)$
θ_1^i	37.710 *** (3.06)	43.140 *** (4.28)
γ_1^i	-4.142 * (2.18)	-1.042 * (0.57)
θ_2^i	-18.560 *** (2.01)	-19.260 *** (2.87)
γ_2^i	21.370 *** (1.80)	16.640 *** (2.03)
LogLik	68150.3	

The index bl and br represent bull and bear markets in the DJIA market, respectively. Clearly, the information of the market volatility is allowed to have different impacts on the probability of selling and buying signals in different market conditions. Thus, the coefficients θ_1^{bl} and θ_2^{bl} (γ_1^{bl} and γ_2^{bl}) indicate how the probability of selling (buying) signals respond to the impact of the information of market volatility, dVR_t and dVR_{t-1}, in bull markets. On the other hand, the coefficients θ_1^{br} and θ_2^{br} (γ_1^{br} and γ_2^{br}) can be interpreted as the market volatility effect on possibility to signal selling (buying) the asset in bear markets.

The results are reported in Table 14. Let us first focus on the significance of the coefficients. As shown in Table 14, $\widehat{\theta}_1 > 0$, $\widehat{\theta}_2 < 0$ and $\widehat{\gamma}_2 > 0$ are found both in bull and bear markets. $\widehat{\gamma}_1$ is insignificant at the 5% significant level, whereas it is negative at the at the 10% significant level. These results indicate that the main findings are unchanged. Second, the asymmetric effects of the information of market volatility emerge in the estimations since we have $|\widehat{\theta}_1^{br}| > |\widehat{\theta}_1^{bl}|$, $|\widehat{\theta}_2^{br}| > |\widehat{\theta}_2^{bl}|$ and $|\widehat{\gamma}_2^{bl}| > |\widehat{\gamma}_2^{br}|$. These results denote that the changes in dVR_t and dVR_{t-1} on selling signals have stronger impact in bear markets, but the effect of the change in dVR_{t-1} on buying signals in bull markets is larger than that in bear markets.

Regarding the economic significance of their impact on trading signals, we found that on average, every 0.1 increase in dVR_t in bear markets increases the probability of generating a selling signal at time t with $\Delta p_t^{01} = 0.805$, while as in bull markets, it enlarges the probability of selling signals with 0.703. In terms of dVR_{t-1}, its 0.1 increase will make the probability to signal selling the asset at time t lower by 0.359 ($\Delta p_t^{01} = -0.359$) in bear markets and 0.346 ($\Delta p_t^{01} = -0.346$) in bull markets. For the impact on buying signals, as dVR_{t-1} increases by 0.1 unit, the probability of a buying signal generated at time t will be increased by 0.298 ($\Delta p_t^{10} = 0.298$) in bull markets and by 0.232 ($\Delta p_t^{10} = 0.232$) in bear markets.

$|\widehat{\theta}_1^{br}| > |\widehat{\theta}_1^{bl}|$ and their results in economic significance denote two things: first, the last value of VR before a selling signal generated at time t (i.e., VR_{t-1}) in bear markets is on average higher than that in bull markets. Second, generating a selling signal at time t in bull markets, more increase in dVR_t is needed, compared to that in bear markets. Here, more increase in dVR_t implies larger variation in price in the period from time t-1 to time t. We can also use the above implication to explain why $|\widehat{\theta}_2^{br}| > |\widehat{\theta}_2^{bl}|$ is found. Based on the assumption that VR_{t-1} before a selling signal in bear markets is higher, it makes sense that the increase in dVR_{t-1} in bear markets has stronger negative effect on the probability of a selling signal generated at time t. Similarly, $|\widehat{\gamma}_2^{bl}| > |\widehat{\gamma}_2^{br}|$ indicates that for the VMA rule, more increase in dVR_{t-1} should be detected to generate a buying signal at time t in bear markets than in bull markets.

3.4 The Value of Market Volatility Ratio in Simple Moving Average Rule

Our intent in this study is to demonstrate that the information of the market volatility is valuable to the moving average system. From last chapter, the SPA results show that the VMA rule enjoys better profitability than the SMA rule. This is one evidence showing that the value of the information of market volatility in the moving average trading system. However, in our SPA tests, the best VMA rule and the best SMA rule are chosen to be compared. These two best rule have different parameter settings and the time they generate trading signals are totally different. Therefore, the worth of the information of market volatility in moving average systems can not be revealed directly.

This paper attempts to investigate the same idea by another method based on the same parameter settings. Our idea is as follows. First, we add the same information of market volatility to several SMA rules with different settings for period n. If the information of market volatility is valuable is forecasting future price movements, it will raise the profitability of the SMA rule no matter what kinds of n the SMA rule set. Thus, we compare the performances of the SMA rule with and without the information of market volatility and check whether the SMA rule with the information of market volatility has higher profitability.

In order to implement the above idea, we adopt the FTP and TVTP Markov-switching model by two reasons. Firstly, it is obvious that the trading strategy of the SMA rule can be measure by the FTP Markov-switching model since its trading mechanism also depends on the crossovers. Secondly, we allow the probability of trading signals generated by the SMA rule to depend on the market volatility ratio by using the TVTP Markov-switching model. Both the VMA and SMA rules use past historical prices to detect future price movements through the crossover mechanism, and the only distinction between these two rules is the way they treat historical prices in forecasting future price movement. The market volatility ratio is a function of past historical prices, therefore, it makes sense that it can exert effects on the generation of the SMA rule's trading signals.

We redefine d_t in the FTP and TVTP Markov-switching model as $p_t - \text{ma}_t$, where ma_t is the logarithm of SMA value at time t of a particular n-day SMA rule and n is selected as 5, 20, 40, 75, 100 and 250, which are one-third of the settings for n. The same information of market volatility is chosen as the VR_t from the best VMA rule in the full sample, $\sigma_t^n/\sigma_t^{ref}$ with $n = 15$ and $ref = 30$. Similarly, z_t in the TVTP Markov-switching model are VR_{t-1}, dVR_t and dVR_{t-1}. AR lag in d_t and the elements in z_t are chosen according to the suggestions by both AIC and SC. Lastly, we make comparison between the profitability of trading signals generated from the FTP Markov-switching model and that from the TVTP Markov-switching model. The trading signals from these two types of Markov-switching model are obtained as follows. Using the full-sample smoothing algorithm of Kim (1994), we can get the smoothing probability of state 0 (rising market, the price line above the SMA line) and state 1(falling market, the price line below the SMA line). We use the smoothing probabilities to infer the rising and falling markets by simply taking 0.5 as the cut-off value for $S_t = 0$ or 1. If the smoothing probability of State 0 at time t is greater (less) than 0.5, it is more likely to be a rising (falling) market at time t. After indexing the full data set as rising-market state or falling-market state, we can get the trading signals through the transition between these two states. A buying signal occurs if the regime of d_t switches from the falling-market state to the rising-market state. Contrarily, the generation of a selling signal comes from the transition from the rising-market state to the falling-market state.

3.4.1 Data and Estimation Results

Table 15 reports the summary statistics of d_t for six n-day SMA rules. We observe that the mean, the maximum, the minimum and the standard deviation of the d_t series get smaller as n is smaller (i.e. the shorter-period SMA rule). On the other hand, the level of kurtosis get rising

Table 15: Descriptive Statistics And Unit Root Tests: d_t From Six SMA Rules

This table reports summary statistics and the unit root tests results for six d_t in the full period. One d_t is defined as p_t minus ma_t, where p_t and ma_t are the logarithm of the DJIA closing price and the SMA value from a particular n-day SMA rule at time t. n is chosen as 5, 20, 40, 75, 100 and 250. For unit root tests, ADF and PP are augmented Dickey-Fuller and Phillips-Perron test statistics. In both tests, the test equation includes the intercept term and the null hypothesis is that the series has a unit root. Test critical values for ADF and PP are -3.443834 (1%), -2.867379 (5%), and -2.569943 (10%). Lags in ADF tests are chosen by Schwartz Bayesian information criterion (SC).

n	5	20	40	75	100	250
Descriptive Statistics						
Mean	0.0004	0.0017	0.0035	0.0067	0.0090	0.0221
Median	0.001	0.004	0.008	0.013	0.017	0.038
Max	0.133	0.294	0.355	0.401	0.386	0.488
Min	-0.251	-0.356	-0.442	-0.516	-0.521	-0.745
Standard Deviation	0.013	0.030	0.043	0.060	0.070	0.116
Skewness	-0.998	-1.141	-1.009	-1.005	-1.052	-1.393
Kurtosis	20.728	14.878	13.041	10.184	8.760	8.146
Unit root tests						
ADF	-43.436	-30.506	-21.286	-14.084	-12.177	-7.195
PP	-58.207	-26.958	-20.254	-15.472	-13.220	-7.579

as n decreases. In other words, the d_t distribution is more concentrated around the mean. The above results come from that as n decreases, the weight of the current price (i.e. p_t) in forming the SMA will be greater. Greater weight on the current price will lessen the gap between the price line and the SMA line and then lead to the d_t series with smaller mean, less standard deviation and higher kurtosis. In addition, in order to implement the estimation of the Markov-switching models, we have to make sure whether these six d_t series are stationary or not. Thus, the conventional unit root tests, ADF test and PP test, are conducted. Clearly, as shown in Table 15, the unit root process is rejected for each series.[14]

Table 16 presents the estimation results for the FTP Markov-switching models. The positive-

[14] The two types of test equations in the ADF and PP test are conducted as follows. One only puts the intercept term in the model. The other contains not only the intercept term but also the trend term. The hypothesis of unit root process is rejected for each series no matter what model of test equation is used.

mean stable and negative-mean volatile state in d_t are still labeled as the rising markets and falling markets, respectively. Similar to the results of d_t from the best VMA rule, $\sigma_1 > \sigma_0$ shows that the SMA rule no matter what n is chosen can not trace the price line closely in the falling markets, compared to in the rising markets. This might be because, the market price in the falling markets is more volatile than that in the rising markets. Moreover, we observe that d_t from the 5-day SMA rule gets smaller σ_1 and σ_0. This result coincides with what we find in Table 15. Except for d_t from the 5-day SMA rule, d_t from other SMA rules in two regimes are quite persistent because we get higher $\widehat{\beta}_{0,1}$ and $\widehat{\beta}_{1,1}$. Lastly, we find that the regime persistence the VMA and six SMA rules expect is alike. Both the VMA and the SMA rules anticipate the rising-market state will persist for 111 days. The regime persistence for the falling-market state the SMA rules expect ranges from 25 days to 28 days, while the VMA rule's expectation is 26 days.

Table 16: The FTP Markov-Switching Models: The SMA Rules

This table presents the estimation results of the Fixed-Transition-Probability (FTP) Markov-Switching model in the full sample for six n-day SMA rules. The value of n includes 5, 20, 40, 75, 100 and 250. The dependent variable in the FTP Markov-Switching Model is d_t, $p_t - \mathrm{ma}_t$. Where ma_t is the logarithm of SMA value at time t of a particular n-day SMA rule. The model is $d_t = \mu_{S_t} + \beta_{S_t,1} d_{t-1} + \epsilon_t$ with $(\mu_0, \sigma_0^2, \beta_{0,1})$ in regime 0 and $(\mu_1, \sigma_1^2, \beta_{1,1})$ in regime 1. $\beta_{S_t,1}$ is the AR1 coefficient in each regime. p^{00} denotes the transition probability of staying in regime 0 while p^{11} denotes the transition probability of remaining in regime 1. The entries in brackets are the standard errors. LogLik represents the value of log-likelihood function.

n	5	20	40	75	100	250
μ_0	0.0003	0.0003	0.0004	0.0004	0.0004	0.0004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
μ_1	-0.0008	-0.0009	-0.0012	-0.0013	-0.0014	-0.0015
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\beta_{0,1}$	0.698	0.928	0.964	0.981	0.985	0.996
	(0.006)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
$\beta_{1,1}$	0.649	0.920	0.959	0.976	0.981	0.990
	(0.012)	(0.006)	(0.005)	(0.003)	(0.003)	(0.002)
σ_0	-0.006	-0.007	0.007	0.007	-0.007	0.007
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
σ_1	-0.018	-0.021	0.022	0.022	0.022	0.022
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
p^{00}	0.991	0.991	0.991	0.991	0.991	0.991
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p^{11}	0.964	0.963	0.960	0.961	0.961	0.961
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
LogLik	71155.60	68006.30	67549.80	67338.30	67294.60	67197.90

The results for the TVTP Markov-switching models reported in Table 17 are very similar to the results in Tables 12. The information of market volatility, dVR_t and dVR_{t-1} resulted from the VR_t series of the best VMA rule, have the same effect on these six SMA rules' trading signals. Firstly, $\widehat{\theta}_1 > 0$, $\widehat{\theta}_2 < 0$ and $\widehat{\gamma}_2 > 0$ are still found. $\widehat{\gamma}_1 = 0$ for the 20-day and 100-day SMA rules while $\widehat{\gamma}_1 < 0$ for the others. Secondly, the estimated values of θ_1, θ_2 and γ_2 all tend to be around the values obtained from the VMA rule. Although we get stronger $\widehat{\gamma}_1$ in the case of the SMA rules, the economic significance of its effect on the probability of buying signals generated is still slight. In addition, it is reasonable that we get similar results for the VMA rule and SMA rules because of using the same information of market volatility.

3.4.2 The Profitability

We make comparison between the profitability of trades from the FTP Markov-Switching model and that from the TVTP Markov-Switching model for six n-day SMA rules, as shown in We also report the performance of these SMA rules' trades from real trading. As mentioned before, the switching of d_t between rising-market state and falling-market states indicates the generation of trading signals. Thus, the number of regime switching reported in Table 18 represents how many trading signals we get from the Markov-Switching models. The profitability of trades from two type of Markov-Switching models are measured by the cumulative return and the daily return with and without cost concerns. The cumulative return illustrates how many profit points we would get in the full period from the trading signals. While the annualized return is obtained from dividing the cumulative return by 81.5, the number of year in the full period. For the cost concerns, we set the one-way transaction cost as 0.05%, a common setting in the literature.

From the results in Table 18, we observe that, for each n-day SMA rule, the profitability of trades from the Markov-Switching models are much higher than that from real trading, and their number of trades are obviously less than that in real trading. This may be because the Markov-Switching model is good to capture the long-term price movements and eliminate the generation of "whiplash" signals. It is not surprising that the total trades from the TVTP model

Table 17: The TVTP Markov-Switching Models: The SMA Rules

This table presents the estimation results of the Time-Varying-Transition-Probability (TVTP) Markov-Switching model in the full sample for six n-day SMA rules. The value of n includes 5, 20, 40, 75, 100 and 250. The dependent variable in the TVTP Markov-Switching Model is d_t, $p_t - \text{ma}_t$. Where ma_t is the logarithm of SMA value at time t of a particular n-day SMA rule. The model is $d_t = \mu_{S_t} + \beta_{S_t,1} d_{t-1} + \epsilon_t$ with $(\mu_0, \sigma_0^2, \beta_{0,1})$ in regime 0 and $(\mu_1, \sigma_1^2, \beta_{1,1})$ in regime 1. $\beta_{S_t,1}$ is the AR1 coefficient in each regime. The time-varying transition probabilities are specified as $p_t^{01}(z_t) = \exp\{\theta_0 + z_t'\theta\}/1 + \exp\{\theta_0 + z_t'\theta\}$ and $p_t^{10}(z_t) = \exp\{\gamma_0 + z_t'\gamma\}/1 + \exp\{\gamma_0 + z_t'\gamma\}$, where z_t represents the information of market volatility and is a 2×1 vector of variables, $z_t = (\text{dVR}_t, \text{dVR}_{t-1})$. θ and γ are 2×1 vectors of coefficients, $(\theta_1, \theta_2)'$ and $(\gamma_1, \gamma_2)'$. The entries in brackets are the standard errors. LogLik represents the value of log-likelihood function.

n	5	20	40	75	100	250
μ_0	0.0003	0.0004	0.0004	0.0005	0.0005	0.0004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
μ_1	-0.0008	-0.0009	-0.0011	-0.0013	-0.0013	-0.0015
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\beta_{0,1}$	0.674	0.918	0.961	0.979	0.984	0.995
	(0.006)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
$\beta_{1,1}$	0.662	0.925	0.961	0.977	0.982	0.991
	(0.012)	(0.007)	(0.005)	(0.003)	(0.003)	(0.002)
σ_0	0.006	-0.007	-0.007	-0.007	0.007	0.007
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
σ_1	-0.018	-0.021	0.022	-0.022	0.022	0.022
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
θ_0	-1.013	-1.108	-1.046	-1.096	-1.074	-1.080
	(0.229)	(0.365)	(1.066)	(0.227)	(0.448)	(0.346)
γ_0	1.562	1.629	1.670	1.630	1.623	1.633
	(0.152)	(0.159)	(0.286)	(0.192)	(0.253)	(0.169)
θ_1	36.490	42.040	39.630	39.490	39.220	39.060
	(2.605)	(3.088)	(10.360)	(1.882)	(3.878)	(2.988)
γ_1	-3.464	-4.728	-4.109	-3.697	-3.546	-3.475
	(1.389)	(3.512)	(1.646)	(0.933)	(2.902)	(1.114)
θ_2	-17.530	-18.870	-18.200	-18.270	-18.200	-18.400
	(1.763)	(1.472)	(2.662)	(1.424)	(2.508)	(1.899)
γ_2	18.180	21.270	19.670	19.420	19.350	19.010
	(1.521)	(2.619)	(3.936)	(1.625)	(2.368)	(1.290)
LogLik	71356.40	68277.30	67801.40	67583.20	67537.70	67439.40

for the n-day SMA rules are all higher than that from the FTP model. Since the price movements that Markov-Switching models detect are long term. As the information of market volatility is allowed to affect the generation of the SMA rule's signals, in a sense that we make the SMA rule also to discover the short term price movements. As a result, the number of trades from the TVTP model is higher. Lastly, for each n-day SMA rule, the trades from the TVTP Markov-Switching model have higher cumulative return and annualized return no matter the transaction cost, compared to that from the FTP model. This result again verifies that the information of market volatility is valuable information in forecasting price movements for technical analysis.

3.4.3 Simple Analysis for Trades

Last section gives us the evidence that as we add the information of market volatility to the SMA rule, the profitability of the SMA rule will be improved. The theoretical benefits of the market volatility ratio in the moving average systems are to take better advantage of the price movement such as earlier/later trading or reducing losses from false trading signals. Thus, in this section, we further compare the trading signals generated from the FTP and TVTP Markov-Switching models one by one in order to investigate its empirical benefits in the moving average systems.

We choose the best results in Table 18, the case for the 250-day SMA rule. Then we compare their trading signals one by one according to their time point of generation. In our SPA tests, we cannot investigate how the information of market volatility affect the prediction for future price movements in technical analysis by comparing the trading signals of the best VMA and best SMA rule. Because these two best rule have different parameter settings and the time they generate trading signals are total different. Here, we focused on the trades for a particular n-day SMA rule and just allow the information of market volatility will affect d_t's probability of switching between states, not affect the value of d_t itself. Therefore, we expect the in-sample prediction from these two models will not be totally different.

According the time point the trading signals generated, we categorize these trades into four types: identical trades, similar trades, overlapping trades and different trades. The identical

Table 18: Comparisons In Profitability Of Trades From The FTP and TVTP Markov-Switching Models

This table presents the performance of the n-day SMA rules' trading signals generated from real trading, from the in-sample predictions of the Fixed-Transition-Probability (FTP) Markov-Switching model, and from that of the Time-Varying-Transition-Probability (TVTP) Markov-Switching model in the full sample. The number of regimes switching in the FTP and TVTP Markov-Switching models indicates the number of trading signals obtained from these two models. One buying signal and one selling signal form a trade. Therefore, 200 trading signals imply the number of trades will be 100. Cumulative return stands for the total profit of all trades in the full sample. Annualized Return is computed from dividing the cumulative return by 81.5, the number of year in the full sample. For the cost concerns, the one-way transaction cost is set as 0.05%.

n-day SMA	Model	No. of Regime Switching	No. of Trades	Cumulative Return (Without cost)	Cumulative Return (With cost)	Annualized Return (Without cost)	Annualized Return (With cost)
$n = 5$	Real Trading		2418	3.966	1.548	4.866%	1.899%
	FTP MS	247	123	7.148	7.024	8.770%	8.619%
	TVTP MS	451	225	7.809	7.583	9.581%	9.304%
$n = 20$	Real Trading		1102	1.782	0.680	2.187%	0.835%
	FTP MS	253	126	7.149	7.023	8.772%	8.617%
	TVTP MS	537	268	7.812	7.544	9.586%	9.256%
$n = 40$	Real Trading		754	1.249	0.495	1.533%	0.608%
	FTP MS	259	129	7.486	7.357	9.130%	9.027%
	TVTP MS	517	258	7.828	7.570	9.546%	9.288%
$n = 75$	Real Trading		515	1.001	0.486	1.228%	0.596%
	FTP MS	265	132	7.340	7.208	9.006%	8.844%
	TVTP MS	505	252	8.003	7.750	9.819%	9.510%
$n = 100$	Real Trading		439	0.978	0.539	1.200%	0.662%
	FTP MS	265	132	7.266	7.134	8.770%	8.753%
	TVTP MS	507	253	7.896	7.643	9.581%	9.377%
$n = 250$	Real Trading		223	1.355	1.132	1.662%	1.389%
	FTP MS	263	131	7.271	7.139	8.921%	8.760%
	TVTP MS	481	240	8.146	7.905	9.995%	9.700%

Table 19: The Number Of Four Types Of Trades From The FTP And TVTP Markov-Switching Models

This table presents the number of four types of trades, the identical, similar, overlapping and different trades, generated from the FTP and TVTP Markov-Switching models for the 250-day SMA rule. The identical trades denotes that both the FTP and TVTP models generate exactly the same trades, while the similar trades represents those trades in which the prediction for the price movement from these two models is quite similar but a little difference. Compared to the FTP model, the TVTP model generates slightly earlier or later signals. The overlapping trades denote the situation that the FTP model forecasts an upward trend for 100 days. During this period, the TVTP model signals to trade three times. For the different trades, it means the FTP and TVTP model generate totally distinct signals. Total trades indicate how many trades the FTP and TVTP model suggest respectively in the full period.

MS Model	Identical Trades	Similar Trades	Overlapping Trades	Different Trades	Total Trades
FTP	13	58	53	7	131
TVTP	13	58	159	10	240

trades represents those trades in which their time to buy and sell suggested by the FTP and TVTP models are exactly the same. For example, both the FTP and TVTP models signal to buy the stock at the 51th day in the full period and sell it after 30 days. The similar trades is a little different to the identical trades. Both the FTP and TVTP models capture the same price movement, but the time they enter or quit the market has slight difference. In other words, the TVTP models may generate signals earlier or later, compared to those in the FTP models. The FTP model suggests to buy the stock at the 43th day and sell it at the 58th day, while the TVTP model generates a buying signal at the 44th day and a selling signal at the 56th day. Both models suggest buying at the 188th day, but the FTP and the TVTP models suggest selling at the 203th and the 204th day, respectively.

The overlapping trades illustrate the situations that the FTP model predicts an upward trend for 40 days from the 2894th day to the 2933th day. While during this period, the TVTP model generates three trades from the 2894th day to the 2899th day, from the 2900th day to the 2922th day, and from the 2924th day to the 2931th day. Or the FTP model generates a buying signal at the 1945th day and a selling signal at the 2080th day, but the TVTP model advise to buy at the 1941th day, sell at the 2020th day, then buy at the 2022th day and sell at the 2078th day. The different trades by definition denotes the trades that their time of generation are mutual

Table 20: Comparisons In The Performance Of Trades Between The FTP and TVTP Model: Similar Trades

This table presents the results that whether the TVTP Markov-Switching model has better performance than the FTP model in the case of similar trades. The similar trades represent those trades in which the prediction for the price movement from these two models is quite similar, but there is slightly difference in their time to enter or exit the market. We split up the similar trades into two groups as the improved group and the deteriorated group according to whether the TVTP model gets higher profit or incurs less loss than the FTP model. The total excess return measures how much more profit the TVTP model gains as it suggests investors to buy or sell the stock earlier/later, compared to the suggestions from the FTP model. Days denotes how many extra days the TVTP has from its earlier and/or later signals, and the daily excess return means the average return gotten by the TVTP model in these extra days.

Performance	Situation	No. of Trades	Total Excess Return From Earlier/Later Trades	Days from Earlier/Later Trades	Daily Excess Return From Earlier/Later Trades
Improved	More profit	27	0.618	131	0.472%
	Less loss	7	0.160	40	0.400%
Deteriorated		24	-0.622	128	-0.486%
All		58	0.156	299	0.052%

distinct. For instance, the FTP model predicts the price rising from the 443th day to the 459th day. However, there exists no trading suggestion from the TVTP model in this period.

Table 19 reports the summary for the number of four types of trades between these two Markov-Switching models. The number of identical trades and similar trades for these two models are 13 and 58, respectively. For the overlapping trades, one trade from the FTP model is on average accompanied by three trades from the TVTP model. The FTP generates seven different trades, while the TVTP model generates tens. Since it doesn't make sense to explore the performance of the identical trades between the FTP and TVTP Markov-Switching models, we do not report the related results and focus on making comparisons in the performance of their similar trades, overlapping trades and different trades, as shown in Table 20, Table 21 and Table 22 respectively.

Similar Trades For similar trades, we separate them into two groups. The first group includes those in which the TVTP model's trading suggestion gets more profit or incurs less loss than the FTP models'. We label them as the improved group. In contrast, the second one is the deteriorated group denoting that the SMA rule does not gain more or lose less from embedding extra information, the market volatility ratio, in future price movement predictions. In Table 20, we report the total excess return that the TVTP model obtains and how many extra days it has from its earlier and/or later signals. For each similar trade, we calculate the excess return that the TVTP model gains through the return of the TVTP model minus that of the FTP model.[15, 16] Then we add those excess returns for all similar trades up and then see how much benefit the TVTP model enjoys for entering/exiting the market earlier/later. The extra days from earlier/later trades for the TVTP model are gotten as follows. If the FTP model signals to buy and sell at the 43th and the 58th day while the TVTP model's signals are generated at the 44th and the 56th day, the extra days the TVTP model have are 3 days. Lastly, the daily excess return represents the average return gotten by the TVTP model in these extra days.

From the results in Table 20, we find that the information of market volatility will not always enhance the performance of the SMA rules for every similar trade. The proportion of the improved group to all similar trades is only 58.62%. However, the SMA rule does benefit from the information of market volatility in the entirety, since, on average, trading one day earlier/later will let investor acquiring more profit, 0.052% a day. In addition, the average of the extra days from the TVTP model's earlier/later trades is 5 days a similar trade.

Overlapping Trades Table 21 presents the comparisons in the performance of the overlapping trades between the FTP and TVTP models. As discussed before, one trade from the FTP model is on average accompanied by three trades from the TVTP model. As matter of fact that, as the FTP model predicts an upward trend for m days (one trade), the maximum and minimum number of trades the TVTP model generates are 13 and 2 during these m days. The above fact in a sense coincides with what we have discussed in section 3.4.2. That is, the price movements

[15] Excess return for an investment in the literature is often defined as the return of that investment minus its cost. Here, we define the excess return as the return of the TVTP model minus that of the FTP model in order to see whether the TVTP model has better predictability for price movements.

[16] There is no need to report the total return of these two Markov-Switching models with cost concerns. Because when we deduct the transaction cost from the return of the TVTP model, the return of the FTP model will be lower by the same amount.

Table 21: Comparisons In The Performance Of Trades Between The FTP and TVTP Model: Overlapping Trades

This table presents the comparisons in the performance of the overlapping trades between the FTP and TVTP models in the full sample. Total return stands for the total profit from all overlapping trades in the full sample. Annualized Return is computed from dividing the total return by days, the number of total days those overlapping trades last. For the cost concerns, the one-way transaction cost is set as 0.05%.

MS Model	No. of Trades	Days	Total Return	Total Return(cost)	Daily Return	Daily Return(cost)
FTP	53	13245	5.022	4.969	0.0379%	0.0375%
TVTP	159	13025	5.590	5.431	0.043%	0.042%
Difference		220	0.568	0.462	0.258%	0.210%

the FTP Markov-Switching model for the SMA rule almost detects are long term. The information of market volatility enables it not only to detect the long term price movements but also to discover the shorter term ones. This may be the reason why the total days the FTP model's trades have are 13245 days, higher than the TVTP model's with 220 days, as shown in Table 21. Although the total days the investors stay in the market are less due to taking the trading suggestions from the TVTP model, its daily return with cost concerns is higher than that from the FTP model with 0.004% (i.e., 0.042%-0.0375%) a day. Further, those 200 days the TVTP model suggests investors to withdraw from the market are found to bring less loss to investors. On average, the reduced daily loss over these days is 0.210%.

Different Trades In Table 21, we compare the performance of different trades between the FTP and TVTP Markov-Switching model. The FTP Markov-Switching model makes seven predictions for price movements. Over the periods of these seven trades, the TVTP Markov-Switching model does not generate any signal. In contrast, there exists no trading suggestion from the FTP Markov-Switching model for ten trades of the TVTP Markov-Switching model. The ratio of different trades to total trades is the least, compared to other type of trades. These different trades also have the smallest average day. On average, one trade from the FTP Markov-Switching model will last for 8 days, while the TVTP Markov-Switching model's will last

Table 22: Comparisons In The Performance Of Trades Between The FTP and TVTP Model: Different Trades

This table reports the comparisons in the performance of the different trades between the FTP and TVTP models in the full sample. Total return stands for the total profit from all different trades in the full sample. Annualized Return is computed from dividing the total return by days, the number of total days those different trades last. For the cost concerns, the one-way transaction cost is set as 0.05%.

MS Model	No. of Trades	Days	Total Return	Total Return(cost)	Daily Return	Daily Return(cost)
FTP	7	58	-0.035	-0.042	-0.060%	-0.072%
TVTP	10	41	0.117	0.107	0.285%	0.261%

for 4 days. We can observe that the performance of the seven trades in the FTP Markov-Switching model is not good with the negative daily return no matter the cost. However, we can gain 0.261% a day on average by the trades in the TVTP Markov-Switching model. We further investigate the performance for each trade in the FTP Markov-Switching model and find that there are four trades that investors will incur losses from them in seven trades. In ten trades from the TVTP Markov-Switching model, the number of trades with positive return is seven. For the results in the similar and overlapping trades, the proportion of trades incurring losses to total trades in the FTP Markov-Switching model are 32.76% and 21.28%, which are relatively lower than that in the different trades (i.e., 57.14%). In the case of the TVTP Markov-Switching model, the ratio for the similar and overlapping trades are 32.76% and 19.15%. Its ratio for the different trades is 30%. The above results imply that the ability of the FTP Markov-Switching model to detect the shorter term price movements is worse than that to forecast long term ones. Furthermore, they also denote that the detection for shorter term price movements can be improved as we use the information of market volatility in forecasting.

3.5 The Future Way of Exploring Explanations for Higher Profits Gained from Market Volatility

The question whether financial assets prices are predictable by technical analysis has its long history. Numerous empirical studies published in last 50 years investigate the profitability of technical trading strategies in terms of the different trading systems, treatment of transaction costs, risk consideration, parameter optimization, data snooping biases reduction, out-of-sample performance's verification and statistical tests application. A bulk of evidences in past studies suggests that using technical analysis helps investors to forecast the market. In addition to exploring whether the technical analysis is profitable or not, another stream in the literature tries to explain why technical trading strategies may generate positive profits in certain speculative markets. Various theoretical and empirical explanations have been proposed.

A broad review of studies about the explanations for technical trading profits can be found in the paper by Park and Irwan (2007). The authors summaries that theoretical explanations for profits stem from market frictions such as noise in current equilibrium prices, trades' sentiments, herding behavior and chaos, and they have been discussed based on four types of models as follows: noisy rational expectations models, behavioral models, herding models and Chaos Theory.[17, 18, 19, 20] In terms of empirical explanations, central bank interventions, order flow, temporary market inefficiencies, risk premiums, market microstructure deficiencies and data snooping have been investigated.[21, 22, 23, 24, 25, 26]

[17] Noise in current equilibrium prices: Hellwig (1982)、Brown and Jeannings (1989)、Grundy and McNichols (1989)、Blume et al. (1994).

[18] Trades' sentiments: De Long et al. (1990a)、De Long et al. (1990b)、Shleifer and Summers (1990).

[19] Herding behavior: Froot et al. (1992)、Schmidt (2002).

[20] Choas: Stengos (1996)、Clyde and Osler (1997).

[21] Central bank interventions: Dooley and Shafer (1983)、Lukac et al. (1988)、LeBaron (1999)、Neely and Weller (2001)、Saacke (2002)、Sapp (2004).

[22] Order flow: Olser (2003)、Kavajecz and Odders-White (2004)、Gehrig and Menkhoff (2004).

[23] Temporary market inefficiencies: Sweeney (1986)、Lukac et al. (1988)、Brock et al. (1992)、Sullivan et al. (1999)、Kidd and Brorsen (2004).

[24] Risk premiums: Lukac and Brorsen (1990)、Kho (1996)、Chang and Osler (1999)、LeBaron (1999)、Sapp (2004).

[25] Market microstructure deficiencies: Greeer et al. (1992)、Day and Wang (2002).

[26] Data snooping: Brock et al. (1992)、Neely et al. (1997)、Sullivan et al. (1999)、White, (2000).

In this study, how the information of market volatility affecting the profitability of technical analysis has been showed, but why the information of market volatility being able to improve technical analysis' performance is not yet discussed. In our future work, we are interested in exploring the explanations for higher profits gained from market volatility. Among the existing literature, there might be two ways of dealing with the question of explanation in higher profits from market volatility.

First, whether the VMA rule has the self-destructive nature could be examined.[27] The self-destructive nature of technical trading rules by the statement of Timmermann and Granger (2004) is that the gains the first users of new technical analysis get are likely short-lived. Once this new technical analysis becomes more widely known and used, its information may get incorporated into prices and then the investors might not get significant profits from this trading rule. In the literature, several studies report that the profits of technical trading rules disappear after their publication (Sweeney, 1986; Lukac et al., 1988; Brock et al., 1992). The self-destructive explanation motives us to think that whether VMA rule's higher profits might stem from its later publication. In order to examine our conjecture, we will conduct the following empirical analyses: 1. Examining whether the static trading rules possess the self-destructive nature. For example, if the MA rule is documented in the academic literature in 1980, we can compare its profitability before and after 1980; 2. Exploring whether the profitability of the VMA rule decline substantially after its publication in 1992; 3. Splitting the data into three parts: before 1980 period, the 1980 1992 period and after 1992 period and exploring whether the higher profitability of the VMA rule still holds in the 1980 1992 period and after 1992 period. If the results reveal that the VMA rule possesses better predictability no matter it is documented in the literature or not, the higher profits of the VMA rule resulting from its less widely using might be excluded.

The second way to figure out the possible explanation for VMA's higher profits depends on risk premium. Technical trading rules getting positive profits might be due to its compensation

[27]The self-destructive nature of technical trading rules is one explanation for the temporary market inefficiencies. Park and Irwin (2007) provide detailed discussion about it.

for bearing risk. Several studies use the Sharpe ratio, the excess returns to standard deviation, as a risk-adjusted performance measure, and find that technical trading rules generate higher Sharp ratios than the buy-and-hold strategy (Chang and Osler, 1999; LeBaron, 1999). Some empirical papers (Kho, 1996; Sapp, 2004) argue that the technical trading returns can be explained by time-varying risk premiums but other studies (Okunev and White, 2003) get opposite results. In our future work, we plan to examine whether the risk premium is the cause of VMA's better predictability by two approaches. The first one is by investigating that whether the VMA rule generates higher Sharpe ratio than other rules by the SPA test. If the Sharpe ratio of the VMA rule is not significantly different from that of other rules, the higher profitability of the VMA rule might be explained as it bears higher risk. Secondly, we can also conduct regression analyses to study whether the return of the VMA rule and other rules can be explained by the risk, and test if the estimated coefficient for the VMA rule is different from that for other rules.

3.6 Conclusion

This chapter, the extension of our study in understand the value of market volatility in technical analysis, seeks to examine empirically how the information of market volatility affects the generation of trading signals. We have proposed a two-state Markov-switching model for the gap between the price line and the VMA line where the dynamics of the state are governed by the information of market volatility.

Using the TVTP Markov-switching model, this paper has presented a significant effect of the information of market volatility on trading signals. The higher the change in market volatility, the higher is the probability of generating a trading signal. Moreover, it has been shown that market volatility seems to have much larger effects on the generation of selling signals during bear-market periods than the effects during bull-market periods. While for the buying signals, its effect is stronger in bull markets than in bear markets. These results may provide evidence to support that the market volatility in technical analysis is designed for taking better advantage of price movements.

In addition, we have considered an investigation that how market volatility alters the signal time and whether the profit improves or deteriorates for a particular simple MA rule. Such investigation enables us to clearly see the relationship between the information of market volatility and the trading signals. Empirical results suggest the signal time changes, stemming from the earlier, later or new signals due to market volatility, will raise the probability in technical analysis.

The main contribution in this paper is that we conquer the difficulty in empirically measuring the nonlinear relationship between the information of market volatility and the trading signals by proposing the TVTP Markov-switching model.

Appendix

The essential but critical part in Pagan and Sossounov (2003) identification for bull and bear markets is to find all turning points in the series, peaks and troughs. To determine turning points, they apply the dating algorithm of Bry and Boschan (BB), which is quite common in the business cycle literature, with two modifications. In Appendix B of their paper, the procedure for programmed determination of turning points are described as follows:

1. **Determination of initial turning points in raw data:**

   The initial turning points in raw data are determined by choosing local peaks (troughs) as occurring when they are the highest (lowest) values in a window 8 months (168 days) on either side of the date. Then the alternation of turns by selecting highest of multiple peaks (or lowest of multiple troughs) should be enforced.

2. **Censoring operations:**

   There are four elimination operations, which are built according to some characteristics of stock markets. First, we eliminate turning points within 6 months (126 days) of beginning and end of series. Then peaks (or troughs) at both ends of series which are lower or higher are dropped. Further, we eliminate cycles whose duration is less than 16 months (336 days). At last, phases whose duration is less than 4 months (84 days) should be eliminated unless the stock price falls(rises) exceeds 20

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