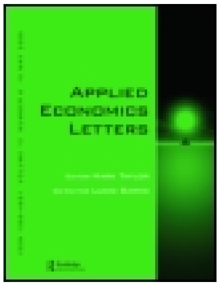

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Incorporating a leading indicator into the trading rule through the Markov-switching vector autoregression model

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Incorporating a leading indicator into the trading rule through the Markov-switching vector autoregression model

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This article examines the profitability of trading rules based on the smoothed probability of Markov-switching models and executes two models in Taiwan's case. The results present that both proposed models can earn excess returns over the buy-and-hold strategy and support that both can be used to trade. However, the univariate Markov-switching model, which only uses daily returns series does not successfully capture the trend in the stock market, especially during a bull market. This implies that high-frequency returns series contain lots of noises. In order to overcome this problem, the Markov-switching vector autoregression model that combines a leading indicator and returns is performed in this study. The results indicate a better trading pattern. We conclude that the leading indicator chosen from open interest in the future market increases useful information and reduces noises to improve model estimation, which can well identify the position of bull and bear markets.

I. Introduction

Efficient market theory illustrates that any information has been reflected in the current price. Hence, no one can beat the market by analysing past price patterns. Ever since the work of Brock *et al*. (1992), however, many studies in the literature provide empirical support for the predictability of asset returns with their trading rules. The usual trading rules are based upon technical analysis (e.g. Brock *et al*., 1992; Mills, 1997) and time series (e.g. Fang and Xu, 2003). Moreover, some research studies about trading rules address the hidden structure and non-linearity of patterns in asset returns (e.g. Fernández-Rodrı́guez *et al*., 2000; Dewachter, 2001; Matilla-García, 2006).

This article also investigates hidden and nonlinear return patterns, and tries to construct a trading rule through Markov-switching models. Dewachter (1996) considers that Markov-switching models imply the current state of the trend and the direction of future movements. Maheu and McCurdy (2000) use a Markov-switching model to capture the nonlinear structure in stock returns. They find that returns can be sorted into two distinct regimes, which are labelled as bull and bear markets. Hence, we propose a trend-following trading rule, in which we buy in a bull market and sell in a bear market, against a 'buy-and-hold' strategy.

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Most studies in the literature about Markov-switching models use low-frequency series data, such as monthly or quarterly data. Studies of trading rules, however, need high-frequency daily returns, because low-frequency series are too insensitive for trading. We consider herein, that there are many stochastic noises in daily returns that cause unsuitable model fitting. Numerous articles applying Markov-switching models to investigate the business cycle combine leading indicators to increase information (Kholodilin and Yao, 2005). Nevertheless, few papers regard leading indicators in the stock market. There are two possible explanations for this: first, the leading indicator is hard to define empirically, because the stock market is usually the leading indicator for other financial indices; second, there is a lack of high-frequency related series. Thus, our article attempts to address a leading indicator and combine it with a Markov-switching model.

As mentioned above, this article introduces a leading indicator in the stock market by applying the Markov-switching vector autoregression (MSVAR) model, in order to construct a trading rule and to examine whether the trading rule can beat buy-and-hold strategy. The valued-weighted Taiwan Stock Index (TAIEX) returns are used as data for analysis.

The rest of this article is organized as follows: Section II illustrates the proposed leading indicator. Section III introduces the MSVAR model. Section IV interprets our trading rule and data sources. Section V presents and discusses the empirical results. Finally, Section VI concludes this article.

II. Leading Indicator

In order to reduce stochastic noises in daily returns and increase information, this article introduces a leading indicator in the stock market. There are some papers about the relationship between economic variables and the stock market. Schaller and van Norden (1997) provide strong evidence that the price/dividend ratio has predictive power for stock market returns, and the response of returns to past price/dividend ratios is asymmetric. Chauvet and Potter (2000) build a latent leading indicator using some financial variables in an autoregressive system. However, these works focus on low-frequency series that may not be suitable for trading.

Our leading indicator is called the long-to-short open interest (OI) ratio which is chosen from the future market and based on two presumptions: first, the future market has a price discovery function, such that the price in the future market leads the price in the spot market; second, the market exists with the phenomenon of information asymmetry, such that large orders (e.g. institutional investors) are informed traders. Fortunately, those presumptions are supported by many studies. Therefore, the long-to-short OI ratio can be calculated by:

$$\frac{1}{\text{OI of the market}} \times \Big(\text{Ten\_OI of a 'buy' position} - \text{Ten\_OI of a 'sell' position}\Big) \tag{1}$$

where Ten_OI refers to the OI of the top ten largest institutional traders. It implies that informed traders expect the prices are in a bull (bear) market when the ratio is greater (less) than zero. There is a another probable explanation: the ratio that is greater (less) than zero is due to informed traders considering that the risk of the market is low (high) for hedging. Hence, we believe the ratio might contain information on the future state of the stock market.

III. Markov-switching Vector Autoregression

Krolzig (1997) proposes the MSVAR model, which extends the univariate traditional Markov-switching model to a multivariate and a vector autoregression process. According to his work, the conditional probability density function for our study of a two-dimensional time series driven by a hidden two-state Markov chain can be represented as:

$$P(y_t|Y_{t-1}, S_t) = \begin{bmatrix} f(y_t|Y_{t-1}, \theta_1) \\ f(y_t|Y_{t-1}, \theta_2) \end{bmatrix} \begin{matrix} \text{if } S_t = 1 \\ \text{if } S_t = 2 \end{matrix} \tag{2}$$

where y_t is a 2×1 vector; Y_{t-1} is the information set available in $t-1$; S_t is the hidden state variable; and θ_1 and θ_2 are the parameter vectors present in each state. Hence, the vector autoregressive model is:

$$\begin{cases} y_t = (1_p, y_{t-1}, \ldots, y_{t-q}) \cdot \beta s_t + u_t \\ u_t|S_t \sim N(0, \Sigma_{s_t}) \end{cases} \tag{3}$$

with

$$\Sigma_{S_t} = \begin{pmatrix} \sigma_{11}(S_t) & \sigma_{12}(S_t) \\ \sigma_{21}(S_t) & \sigma_{22}(S_t) \end{pmatrix} \tag{4}$$

where u_t is an error term which follows i.i.d. normal distribution with zero mean and Σs_t is the generalized covariance matrix. Moreover, the transition probability is defined as:

$$p_{ij} = P(S_t = j|S_{t-1} = i), \quad \text{for } i,j = 1,2 \tag{5}$$

The duration of state i is calculated by $1/1 - p_{ii}$. This MSVAR model can be estimated by the EM algorithm.

IV. Trading Rule and Data

If the MSVAR model can successfully identify the turning points of bull and bear markets, then we would buy at the starting point of a bull market and sell at the end. Krozig (2003) suggests that the turning points can be captured using the smoothed probability estimated from MSVAR. Therefore, buy signals are generated sequentially at the starting point of a bull market and sell signals are generated sequentially when turning into a bear market:

$$\tau_i^B \equiv \inf\{t+1 : \mathrm{P}(s_t^* = \text{bull}|\,Y_T; \hat{\theta}_T) > 0.5\} \tag{6}$$

$$\tau_i^S \equiv \inf\{t+1 : \mathrm{P}(s_t^* = \text{bear}|\,Y_T; \hat{\theta}_T) > 0.5\} \tag{7}$$

where τ_i^B and τ_i^S are buy signals and sell signals, respectively; and $\mathrm{P}(s_t^* = \text{bull}|\,Y_T; \hat{\theta}_T)$ and $\mathrm{P}(s_t^* = \text{bear}|\,Y_T; \hat{\theta}_T)$ are the smoothed probabilities for bull and bear markets, respectively.

The return data used in this study are daily TAIEX returns (*Return*) from 1 July 2004 to 1 December 2006. They are provided by Taiwan Stock Exchange Corporation. The mean return of the TAIEX is 0.044% per trading day (or 16% per year). The open interests of the top 10 largest institutional traders (*Ten_OI*) are provided from Taiwan Futures Exchange. In order to avoid the discontinuity problem of the settlement month, we use all settlement months' open interest data.

V. Empirical Results and Discussion

We perform the Dickey–Fuller test for the presence of unit roots in *Return* and *Ten_OI*. The results for both indicate that the test significantly rejects the null hypothesis of the series with unit root at the 5% level. In addition, we use the Granger causality test to confirm the relationship between *Return* and *Ten_OI*. The result illustrates *Ten_OI* granger-causes *Return* (p-value < 0.01), but *Return* does not granger-causes *Ten_OI* (p-value = 0.36). It verifies that *Ten_OI* can be the leading indicator in the stock market and contains useful information to reduce stochastic noises in daily return.

This article examines the profitability of two different MSVAR models: Model 1 (MSI(2)H-AR(0)) supposes that there is a two-state, heteroskedastic covariance and only uses daily returns. Model 2 (MSI(2)H-VAR(0)) combines the leading indicator and return series. Table 1 gives the results of the MSVAR estimation, and the profitability of our trading rule in both models is presented in Table 2.

Model 1 with only return series

Model 1 in Table 1 represents two distinct states. The standardized mean return of State 1 is negative and that of State 2 is positive, while these parameters are not significant. The variance of State 1 is much higher than State 2. These characteristics of the two states are in line with Maheu and McCurdy's (2000) results. We, therefore, label States 1 and 2 as the bear and bull markets, respectively. Table 1 shows the average durations of bear and bull markets to be 3.75 and 21.74 days, respectively.

Model 1 in Table 2 shows that the bull market is 10 times longer than the bear market and the number of trades, when new trading signals arrive to shift the state is 28. The daily return in a bull market identified

Table 1. Estimation results of MSVAR models

	Model 1	Model 2	
	Return	Return	Ten_OI
β_1	−0.386 (0.241)	−0.136 (0.067)**	−0.922 (0.047)***
β_2	0.066 (0.043)	0.105 (0.055)*	0.712 (0.036)***
σ_1	2.758 (0.669)***	1.041 (0.108)***	0.403 (0.037)***
σ_2	0.668 (0.059)***	0.940 (0.087)***	0.294 (0.026)***
p_{11}	0.733 (0.113)***	0.969 (0.011)***	
p_{22}	0.954 (0.022)***	0.978 (0.008)***	

Notes: Numbers in parentheses are SEs.
*, ** and ***Significant at the 10, 5 and 1% levels, respectively.

Table 2. Results for MSVAR trading rules

	N(bull)	N(bear)	N(trade)	Bull	Bear	Bull–Bear
Model 1	547	55	28	0.00087 (0.761)	−0.00363 (2.997)***	0.00450 (3.300)***
Model 2	340	262	17	0.00160 (1.782)*	−0.00106 (2.120)**	0.00266 (3.379)***

Notes: N(bull) and N(bear) are the numbers of bull and bear markets days, respectively. N(trade) is the number of trades, while the numbers in parentheses are t-statistics for testing the difference from the unconditional mean return hypothesis. *, ** and ***Significant at the 10, 5 and 1% levels, respectively.

from Model 1 is about 0.087%, and the daily return in a bear market is −0.363%. We perform t-statistics as proposed by Brock *et al.* (1992) to test the null hypothesis, such that the daily return significantly differs from the unconditional mean return which is 0.044%. The results illustrate that the daily return in a bear market is less than the unconditional mean, while the daily return in a bull market is not significantly larger than the unconditional mean. The quantity 'Bull-Bear', which measures the profitability for excess returns over the 'buy-and-hold' strategy, is significant at the 1% level.

These results imply that Model 1 cannot successfully capture the position of a bull market, though this trading rule does beat the buy-and-hold strategy. The duration of a bear market is extremely and unreasonably shorter than a bull market. One explanation for this is that the stochastic noises in the daily return result in a lack of estimation information. Therefore, Model 2 combines the leading indicator and returns in order to reduce noises.

Model 2 with both a leading indicator and returns series

Table 1 shows that the characteristics of two states estimated from Model 2 are similar to Model 1, such that the standardized mean return of State 1 is negative, that of State 2 is positive, and the variance of State 1 is larger than State 2. We also find that the mean *Ten_OI* ratio is negative in a bear market and positive in a bull market. This finding is consistent with our claim. Table 1 shows the average durations of bear and bull markets to be 32.26 and 45.45 days, respectively.

Model 2 in Table 2 identifies the bull and bear markets to have total of 340 and 262 days, respectively. The daily return in a bull market is 0.16%, and the daily return in a bear market is −0.106%. Although the daily return in a bear market of Model 2 is higher than in Model 1, the daily returns in the two states both significantly differ from the unconditional mean. This reveals that the Model can capture very well the bull and bear markets. The number of trades obviously decreased so as to save on transaction costs. The result also indicates that this trading rule is better than the buy-and-hold strategy.

We further find the 'break-even cost', which is the cost that absorbs the excess returns over the buy-and-hold strategy (Fang and Xu, 2003), is 4.826% for Model 2 and 2.404% for Model 1. Comparing to Model 1, Model 2 (which combines the leading indicator) presents a more reasonable profitability of stock returns. We believe that the leading indicator contains information to improve the estimation result and reduces noises in daily prices.

VI. Concluding Remarks

In this article, we consider whether the Markov-switching model can successfully identify bull and bear markets in stock prices. Therefore, the purposes of this study are to examine the profitability of trading rules based on Markov-switching models and to introduce a leading indicator for better estimation. According to different specification, two models are considered: One is a univariate Markov-switching model, which only uses daily returns series. The other is a MSVAR model that combines returns and a leading indicator, which implies informed traders' expectation for the direction of future movements.

The results show that both proposed models can earn excess returns over the buy-and-hold strategy. However, the former model does not successfully capture the turning points in a stock market, especially for a bull market. This implies high-frequency returns series contain many noises. After combining a leading indicator, the latter model presents a better trading pattern. We conclude that the leading indicator is able to increase useful information and reduce noises in order to improve the model estimation. Our trading rule depends on the smoothed probability estimated from the MSVAR model. Though the results show satisfaction, the model does need more information about market. For example, an extended sample size or other suitable related series may improve trading profits.

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