E C O N O M I C S   B U L L E T I N

Demarcating stable and turbulent regimes in Taiwan's stock market

Yu-Lieh Huang
National Tsing-Hua University

Chia-Wen Ho
University of North Carolina at Charlotte

Abstract

Various trading rules involving derivatives have been widely applied by practitioners under a wide range of market conditions; to date, however, few econometric models can provide a way to accurately decide when to apply those strategies. In this paper, we employ the Innovation Regime-Switching (IRS) model (Kuan, et al, 2005, JBES) to separate stock price sample periods into stable and turbulent regimes on the basis of their dynamic behaviors. Our results show that, based on regime identification, we can obtain satisfactory profits by implementing appropriate and timely derivative strategies.

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1 Introduction

"Buy Low and Sell High" is a well-known, conventional strategy in the stock market, by which investors technically buy a stock when it appears to be "bullish" and sell it when it seems to be "bearish". But, the crucial part of this strategy lies in the timing of buying and selling dates which are known as the change-points between a bull and a bear regime. Thus, the identification and the prediction of the change points in bull/bear regimes are critical for market analysts. In the extant literature, the presence of regime-switching in stock market returns is usually determined by Markov-Switching (MS) models. Pagan and Sossounov (2003), for example, employ MS models to identify persistent bull/bear regimes in stock markets. To cite another example, Maheu and McCurdy (2000) propose a variant of the MS model and characterize the bull (bear) market as high (low) returns coupled with low (high) volatility in their revised MS model. Also worth noting, Chauvet and Potter (2000) construct a nonlinear coincident stock indicator driven by an MS model and Chen (2008) employes an MS unit root regression model to investigate the issue of the non-stationarity and non-linearity of OECD stock prices.

Largely due to rapid developments in the financial market, numerous investment strategies involving derivatives have been put forth. These strategies may generate significant profits not only in bull/bear markets, but also in markets with more complicated conditions. For example, if an investor is expecting a large movement in a stock price (but he/she does not know in which direction the move will be), a straddle-purchase strategy, or a 1:2 hedging strategy, might be adopted to obtain profits.[1] By contrast, the reverse positions of these strategies may yield profits if the investor is betting that the stock price is only going to fluctuate slightly around some specified price. The main objective of these strategies, therefore, is to identify and predict the change points between *stable* and *turbulent* regimes. With the identification of these two regimes, we can use these strategies more precisely. From an econometric point of view, a stock price may fluctuate slightly and behave like a stationary process when the market is in a stable regime; against this, it may have large swings and behave like a random walk process when the market is turbulent. Hence, a time series model that allows for distinct (unit-root and stationary) dynamics in different periods is required to identify the change points between these two types of regime.

In this paper, we analyze stable and turbulent markets by using the Innovation Regime-Switching (henceforth IRS) model recently developed in Kuan et al. (2005), and we demonstrate how such a modelling framework can be constructed to evaluate trading strategies in these markets. The IRS model is an unobserved-component model consisting of a random walk with a drift component and a trend-stationary component; whether a particular component is activated depends on an unobservable state variable whose law of motion is governed by certain probability laws. Thus, the dynamic patterns in an IRS process are not necessarily fixed at all times, and may alternate from time to time. Since the IRS model can accommodate both stationary and nonstationary behaviors at different time periods, it can

[1] A straddle-purchase strategy, denoted as $+\mathbf{C}+\mathbf{P}$, involves buying a call and a put at the same strike price. A 1:2 hedging strategy, denoted as $-\mathbf{S}+2\mathbf{C}$, consists of a short position in a stock plus two long positions in a call. The reverse positions of these strategies are denoted as $-\mathbf{C}-\mathbf{P}$ and $+\mathbf{S}-2\mathbf{C}$, respectively.

serve as a practical tool and provide useful information for the investors before they adopt the strategies.

We apply the IRS model to Taiwan Semiconductor Manufacturing Company (hereafter TSMC) and Fubon Financial Holding Company (henceforth Fubon) daily stock prices.[2] We find that, during the entire sample period, unit-root nonstationarity is likely to be the prevailing dynamic pattern about 70% (60%) of the time in TSMC (Fubon) stock prices, whereas weak stationarity is likely to prevail for the remaining movements. That is, movements in TSMC (Fubon) stock prices can be classified into two distinct regimes. These findings are quite different from the conclusions drawn from either a random walk model (e.g., Samuelson, 1965) or mean-reverting model (e.g., Summers, 1986) in which only one model structure is permitted throughout the entire sample period. More than that, our simulation results show that, for the most part, the proposed trading strategies outperform the buy-and-hold strategy in both stable and turbulent episodes even when transaction costs are taken into account.[3] These results are in line with those in Fernández et al. (2000) where they apply nonlinear predictors to the General Index of the Madrid Stock Market.

This paper is organized as follows. In Section 2, we illustrate the basic concepts of the IRS model and briefly discuss the trading strategies. Section 3 presents the empirical analysis of TSMC and Fubon stock indices based on the IRS model, and Section 4 concludes this paper.

2 The IRS Model and the Trading Strategies

The IRS model is an unobserved-component model consisting of a random-walk component and a stationarity component such that there is a switching mechanism that determines the prevailing component at a particular time. More specifically, suppose that stock price P_t is the sum of two unobserved components – namely, $P_t = P_{1,t} + P_{0,t}$ such that

$$\begin{aligned} \Delta P_{1,t} &= \alpha_0 + s_t \upsilon_t, \\ \Psi(B) P_{0,t} &= \Phi(B)(1 - s_t)\upsilon_t, \end{aligned} \tag{1}$$

where υ_t is an i.i.d. random sequence with mean α_1 and variance σ_υ^2; $s_t = \{0, 1\}$ is a two-state, first-order Markov chain with the transition probabilities $p_{00} = \mathbb{P}(s_t = 0 \mid s_{t-1} = 0)$ and $p_{11} = \mathbb{P}(s_t = 1 \mid s_{t-1} = 1)$; the term $\Delta P_{1,t} = P_{1,t} - P_{1,t-1}$ is the change in the first component $P_{1,t}$; and $\Psi(B) = 1 - \psi_1 B - \cdots - \psi_m B^m$ and $\Phi(B) = 1 - \phi_1 B - \cdots - \phi_n B^n$ are the polynomials in the lag operator of order m and n, respectively. It is readily seen that the first component $P_{1,t}$ essentially follows a random-walk model with drift term α_0, while the second component $P_{0,t}$ serves as a stationary ARMA(m, n) model. Thus, this model can

[2] TSMC is the world's largest semiconductor foundry. The company's manufacturing capacity is currently about 4.3 million wafers, while its revenues represent some 50% of the global foundry market. Fubon Financial is the first holding company listed on the Taiwan Stock Exchange. We also apply the IRS model to other stock prices (e.g., United Microelectronics Corporation, Mega Financial Holding Company) and obtain similar results. These results are not reported but available upon request.

[3] We wish to underscore the practicability of the new derivative strategy operating in conjunction with the IRS model. For comparison, in this study, we choose the buy-and-hold strategy as the typical traditional strategy.

be referred to as an IRS$(1; m, n)$ model, signifying that it is a combined random-walk and ARMA(m, n) model.

A key feature of this IRS model (1) is that it allows the innovation state to switch with time; only one component is activated at a time, depending on the realization of the state variable s_t. When $s_t = 1$, the first component $P_{1,t}$ is excited by υ_t, while $P_{0,t}$ evolves without this innovation. As long as $s_t = 1$, the innovation υ_t has a permanent effect on future stock prices P_{t+j} $(j > 0)$ and generates unit-root type dynamics. In this case, the movements in stock prices are said to be in turbulent regimes. When $s_t = 0$, however, the second component $P_{0,t}$ is excited by υ_t, but $P_{1,t}$ grows along a linear trend $\alpha_0 t$ without the new innovation; hence, υ_t exerts only a transitory effect on future stock prices and results in a trend-stationary pattern. In this case, the movements in stock prices are said to be in stable regimes. If there is no absorbing state, s_t assumes different values over time. What this means is that the dynamic patterns of P_t are permitted to alternate from time to time and exhibit both nonstationary and trend-stationary behaviors in different periods.

There are different ways to estimate the IRS$(1; m, n)$ model. By setting $\upsilon_t = \alpha_1 + \varepsilon_t$, we follow Huang (2006) and write the process (1) in an ARMA process with MA random coefficients:

$$\Psi(B)(1-B)P_t = \alpha_0 \Psi(1) + \sum_{i=1}^{\gamma+1} \xi_{i,s_{t-i}}(\alpha_1 + \varepsilon_{t-i}) + (\alpha_1 + \varepsilon_t), \tag{2}$$

where $\gamma = \max\{m, n\}$,

$$\xi_{1,s_{t-1}} = \begin{cases} -\psi_1, & \text{if } s_{t-1} = 1, \\ -1 - \varphi_1; & \text{otherwise,} \end{cases} \qquad \xi_{i,s_{t-i}} = \begin{cases} -\psi_i, & \text{if } s_{t-i} = 1, \\ \varphi_{i-1} - \varphi_i; & \text{otherwise,} \end{cases}$$

for $i = 2, \ldots, \gamma$, and the last coefficient is

$$\xi_{\gamma+1,s_{t-\gamma-1}} = \begin{cases} 0, & \text{if } s_{t-\gamma-1} = 1, \\ \varphi_r; & \text{otherwise,} \end{cases}$$

$\psi_i = 0$ for $i > m$ and $\varphi_i = 0$ for $i > n$. The approximate quasi-maximum likelihood estimates (QMLE),

$$\boldsymbol{\theta} = (\psi_1, \ldots, \psi_m, \varphi_1, \ldots, \varphi_n \alpha_0, \alpha_1, \sigma_\varepsilon^2, p_{00}, p_{11})',$$

can then be found using a numerical-search method. Our program is written in GAUSS which employs the Broyden-Fletcher-Goldfarb-Shanno (BFGS) search algorithm. By applying the estimation algorithm in Huang (2006), we obtain the filtering probabilities $\mathbb{P}(s_t \mid \boldsymbol{\Omega}^t; \boldsymbol{\theta})$, the prediction probabilities $\mathbb{P}(s_{t+1} \mid \boldsymbol{\Omega}^t; \boldsymbol{\theta})$ and the quasi-log-likelihood function as by-products, where $\boldsymbol{\Omega}^t = \{P_1, \ldots, P_t\}$ is the collection of all the observed variables up to time t.

To demonstrate the applicability of the IRS model (1), we use the filtering probabilities to identify stable and turbulent periods and take 0.5 as the cut-off value for $s_t = 0$ or 1. That is, periods with the filtering probabilities of $s_t = 0$ greater (less) than 0.5 are more likely to be in stable (turbulent) regimes. To investigate whether stable and turbulent regimes

Table 1: Call/put warrants of TSMC and Fubon stocks.

Underlying Asset: TSMC			Underlying Asset: Fubon		
Warrant	Strike Price	Listed/Maturity	Warrant	Strike Price	Listed/Maturity
Fubon 19 (call)	53.40	2002.10.23/2003.10.22	Yuanta70 (call)	21.6	2003.2.26/2003.11.5
Yuanta52 (call)	72.75	2002.9.24/2003.9.23	Barits12 (call)	35.84	2003.8.18/2004.2.17
Yuanta76 (call)	59.00	2003.7.9/2004.1.8	YuantaB3 (call)	28.9	2003.9.10/2004.3.9
Yuanta77 (put)	59.00	2003.7.9/2004.1.8	YuantaB4 (put)	28.9	2003.9.10/2004.3.9

provide valuable economic signals in the stock market, we also examine the profitability of two simple trading strategies based on the prediction probabilities. That is, we use a value of $\mathbb{P}(s_{t+1} = 0 \mid \boldsymbol{\Omega}^t; \boldsymbol{\theta})$ being greater than 0.5 (i.e., the next period is more likely to be in a stable regime) as a sell signal of a straddle-purchase strategy or a 1:2 hedging strategy in the current period, while we use a value of $\mathbb{P}(s_{t+1} = 0 \mid \boldsymbol{\Omega}^t; \boldsymbol{\theta})$ being less than 0.5 as a signal to initiate the reverse position of these strategies. We compute the average daily rate of returns (hereafter DRR) of each stock for all trading strategies using warrant data and estimated reasonable stock option prices.

3 Empirical Study

We now apply the IRS model (1) to TSMC and Fubon daily share prices. The data, along with call and put warrants (of which the underlying assets are the two stocks), are taken from the Taiwan Stock Exchange Corporation from April 1, 2003 to January 16, 2004 for a total of 204 observations.[4] Due to the inactive options market in Taiwan, there are only three (one) covered call (put) warrants contingent on TSMC stock and eight (one) covered call (put) warrants contingent on Fubon stock during the sample period. Table 1 lists the names, strike prices and listed and maturity dates of the warrants used in this paper; we omit data that are not used.

We first estimate an array of IRS$(1; m, n)$ models for TSMC and Fubon stock prices with m and n no greater than 4. We estimate the parameters using the algorithm described in Huang (2006). This algorithm is initialized using a broad range of random initial values. The covariance matrix of $\hat{\boldsymbol{\theta}}$ is $-\boldsymbol{H}(\hat{\boldsymbol{\theta}})^{-1}$, where $\boldsymbol{H}(\hat{\boldsymbol{\theta}})$ is the Hessian matrix of the log-likelihood function evaluated at the QMLE $\hat{\boldsymbol{\theta}}$. Among all the models we consider, both the Akaike information criterion (AIC) and the Schwartz Bayesian information criterion (SIC) select the IRS$(1; 2, 2)$ model for TSMC and Fubon stock prices. The estimated results are summarized in Table 2.

We then conduct some diagnostic tests on the estimated models, including the Ljung-Box (1978) Q test and the LM test of Engle (1982) on the ARCH effect. The resulting

[4] We start our empirical study on April 1st because of the data constraint of put warrants. The last analysis date is January 16, 2004 which is the last trading day before the Chinese New Year (11-day vacation) in Taiwan.

Table 2: QMLEs of the IRS(1; 2, 2) model.

	TSMC			Fubon		
Parameters	Estimate	Standard error	t statistic	Estimate	Standard error	t statistic
α_0	-0.890	0.278	-3.201*	0.023	0.170	0.135
α_1	0.955	0.259	3.687*	0.031	0.080	0.387
ψ_1	0.103	0.280	0.367	0.394	0.132	2.984*
ψ_2	-0.279	0.103	-2.708*	-0.160	0.241	-0.663
φ_1	-0.312	0.130	-2.400*	-0.281	0.110	-2.554*
φ_2	-0.212	0.257	-0.824	-0.212	0.193	-1.115
σ_v	0.952	0.043	22.136*	0.556	0.120	4.633*
p_{00}	0.623	0.122		0.789	0.130	
p_{11}	0.815	0.110		0.862	0.091	
	Log-likelihood = 299.43			Log-likelihood = 141.34		
	AIC (SIC) = 612.67 (642.09)			AIC (SIC) = 300.99 (300.81)		

Note: t-statistics with an asterisk are significant at the 5% level.

statistics for the residuals $\hat{\varepsilon}_t$ are $Q(20) = 12.885$ and $\text{ARCH}(2) = 0.129$ for TSMC and $Q(20) = 22.185$ and $\text{ARCH}(2) = 0.134$ for Fubon. These statistics are all insignificant at the 5% level under the $\chi^2(20)$ and $\chi^2(2)$ distributions, respectively. Hence, there appears no serial correlation or conditional heteroskedasticity in these residuals. Following Engel and Hamilton (1990), we also test whether the state variables s_t are independent over time; this amounts to testing whether $p_{00} + p_{11} = 1$. The resulting Wald statistics is 9.375 (19.148) for TSMC (Fubon) stock prices, and the null hypothesis of $p_{00} + p_{11} = 1$ is rejected at the 1% level under the $\chi^2(1)$ distribution. The rejection of the null hypothesis justifies our Markovian specification of the state variable.

Since many studies have established that the stock price may contain a unit root (e.g., Samuelson, 1965), it is imperative to test whether the analyzed stock price follows an IRS process against the null that it follows a difference stationary process. In the present context, this amounts to testing whether $p_{11} = 1$. Under the null hypothesis, the transitory component $P_{0,t}$ does not enter the model so that the nuisance parameter (e.g., p_{00}) is not identified. In this case, standard likelihood-based tests, such as Wald, LM, and likelihood ratio tests, are not applicable, as discussed in Davies (1977, 1987) and Hansen (1996).[5] To circumvent this problem, we adopt the simulation-based test proposed by Kuan et al. (2005). We first estimate an array of ARIMA $(\kappa, 1, \ell)$ models with κ and ℓ no greater than 4 and choose an appropriate specification based on AIC. The ARIMA model selected is:

$$\Delta P_t = \underset{(0.068)}{0.103} + \underset{(0.231)}{0.697}\Delta P_{t-1} - \underset{(0.071)}{0.249}\Delta P_{t-2} - \underset{(0.236)}{0.556}\epsilon_{t-1} + \epsilon_t \tag{3}$$

[5] Recently, Hansen (1992), Garcia (1998) and Carrasco et al. (2004) have proposed several solutions to test parameter stability in a Markov-switching model. However, their solutions cannot be directly applied to our problem because the primary concern here is to check whether $p_{11} = 1$, not parameter stability.

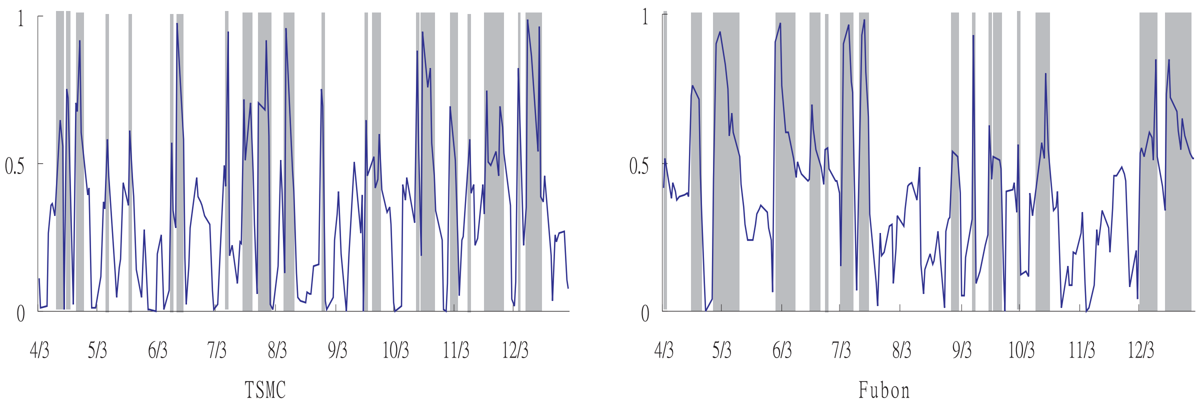

Figure 1: Estimated filtering probabilities of $s_t = 0$ for TSMC and Fubon.

with $\sigma_\epsilon^2 = 1.161$ for TSMC and

$$\Delta P_t = \underset{(0.036)}{0.034} + \underset{(0.747)}{1.747}\Delta P_{t-1} - \underset{(0.751)}{0.170}\epsilon_{t-1} + \epsilon_t \tag{4}$$

with $\sigma_\epsilon^2 = 0.504$ for Fubon, where the standard error of each estimated coefficient is listed in parentheses. We re-estimate the IRS(1; 2, 2) model using the data generated from equation (3) (equation (4)) and obtained a finite-sample reference probability of $\tilde{p}_{11}$. With 1000 replications, we obtain an empirical distribution of $\tilde{p}_{11}$. We then compare the estimation result of $p_{11} = 0.815$ for TSMC ($p_{11} = 0.862$ for Fubon) in Table 2 with the quantiles of this empirical distribution. The empirical p-value of p_{11} is 0.042 (0.039). The null hypothesis that the analyzed stock price follow an ARIMA processes is rejected at 5% level. The IRS model, therefore, fits the data well.

In Figure 1, we plot the estimated filtering probabilities of $s_t = 0$ for the TSMC and Fubon stock prices. It is abundantly clear that stock price is more likely to be in a stable regime when probability is closer to 1. If 0.5 is taken as the discriminating value, we find that there are 53 periods (about 26% of the whole sample period) with estimated filtering probability $\mathbb{P}(s_t = 0 \mid \mathbf{\Omega}^t) > 0.5$ in the case of TSMC and 68 periods (about 33% of the sample) in the case of Fubon. To facilitate our analysis, the stable regimes, identified on the basis of the above criterion, are shaded in Figure 1. Compared with that of Fubon, the stock price of TSMC stays in stable regimes for shorter periods. That is, it is much less frequent that TSMC stock price remains within stable price intervals. This makes good sense from the financial perspective. Since TSMC is one of the leading companies in Taiwan's electronic industry, it is better known to the public and considerably more popular among investors, with the result being that more investors buy and sell TSMC stock, which prevents its price from staying in stable regimes.

To understand the prediction ability of the model, we also plot the one-step-ahead prediction probability of a stable regime, i.e.,

$$\mathbb{P}(s_{t+1} = 0 \mid \mathbf{\Omega}^t) = p_{00}\,\mathbb{P}(s_t = 0 \mid \mathbf{\Omega}^t) + p_{11}\,\mathbb{P}(s_t = 1 \mid \mathbf{\Omega}^t).$$

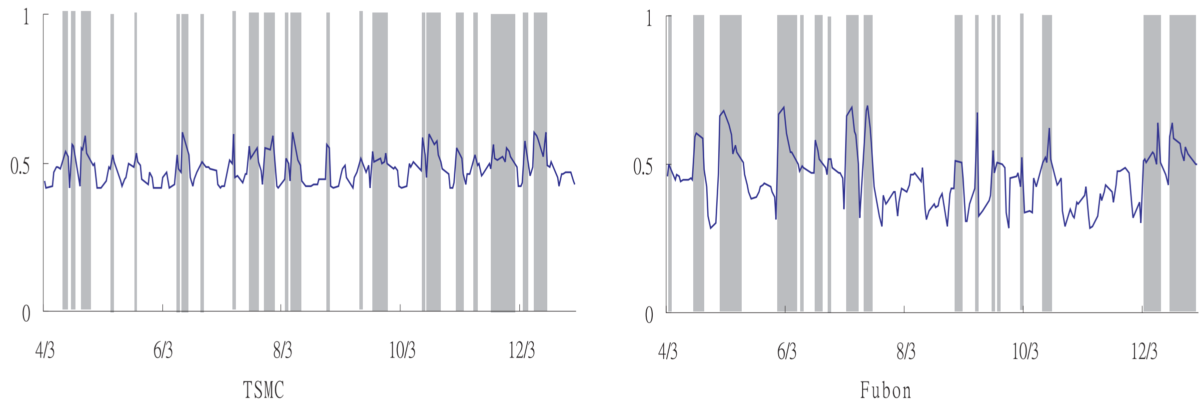

Figure 2: Estimated prediction probabilities of $s_t = 0$ for TSMC and Fubon.

In Figure 2, the panel of the left shows the estimated results for TSMC and that on the right, those for Fubon. Here, 0.5 is again taken as the cut-off value. Probability greater (less) than 0.5 indicates that stock prices are more likely to be in a stable (turbulent) regime in the following period. It can be seen that the estimated prediction probability mainly varies between 0.41 and 0.63 in the case of TSMC and between 0.28 and 0.72 in the case of Fubon. These results imply that with available information up to the current period, investors can be more confident about differentiating between stable and turbulent regimes for Fubon stock prices. One reasonable explanation for this might be that TSMC is better known in the stock market, and this could open it up to more information, both good and bad news, which would surely have an impact on its stock price. As a result, stock price movements are apt to be less predictable.

We now proceed to compute the average DRR based on these prediction probabilities. We use data for the warrants most nearest to at-the-money to build trading strategies. It is well known that when adopting the proposed strategies, more return can be earned only by choosing at-the-money warrants. To confirm the profitability of our results, we also compare the DRR with those of the buy-and-hold strategy. Table 3 compares the results of different trading strategies and takes transaction costs into account.[6] In the case of TSMC, it can be seen that, except for the straddle-sale strategy ($-\mathbf{C}-\mathbf{P}$) in the stable regime, the proposed trading strategies all outperform the buy-and-hold strategy in all periods. But, it should be noted that, in the case of Fubon, these strategies may yield large negative DRR. The reason that these strategies have an inferior performance in the case of Fubon is that the exercising prices of the warrants deviate greatly from stock prices in each regime. Data for the at-the-money warrants are seldom found in Taiwan's market.

To overcome this problem, we simulate reasonable stock option prices based on the Black-

[6] To make the portfolios more close to reality, we take the transaction cost into account. When the investors change their positions of portfolio, for example, from long position to short position, they should be charged the securities transactions tax 0.1425% and transactions fee 0.3%.

Table 3: Comparison of the average DRRs of the trading strategies based on the warrants.

	TSMC			Fubon		
Trading Rules	Whole Period	Turbulent	Stable	Whole Period	Turbulent	Stable
Straddle:	0.263%	–	–	−0.935%	–	–
Purchase (+**C**+**P**)	–	0.573%	–	–	−1.134%	–
Sale (−**C**−**P**)	–	–	−0.351%	–	–	−0.320%
1:2 hedging:	0.455%	–	–	0.031%	–	–
Purchase (−**S**+**2C**)	–	0.344%	–	–	0.078%	–
Sale (+**S**−**2C**)	–	–	0.811%	–	–	−0.053%
Buy-and-hold:	0.135%	0.261%	−0.251%	0.123%	−0.063%	0.201%

Note: A straddle-purchase strategy (+**C**+**P**) involves buying a call and a put at different strike prices. A 1:2 hedging purchase strategy (−**S**+**2C**) consists of a short position in a stock plus two long positions in a call option. The reverse positions of these strategies are denoted as −**C**−**P** and +**S**−**2C**, respectively. Transaction costs are taken into account.

Scholes formula:

$$P_C = S\Phi(d_1) - Ke^{-rT}\Phi(d_2),$$
$$P_P = Ke^{-rT}\Phi(-d_2) - S\Phi(-d_1),$$

where P_C (P_P) is the estimated price of a call (put) option; S is the daily closing stock price; K is the exercising price set based on market conditions; $r = 1.4\%$ is the one-year average deposit interest rate of the five major banks announced by the Central Bank of Taiwan in 2003; T is the maturity date; $\Phi(\cdot)$ is the cumulative normal distribution; σ is the standard deviation calculated by the real stock return; and

$$d_1 = \frac{\ln\big(S/K\big) + \big(r + \sigma^2/2\big)T}{\sigma\sqrt{T}}, \quad d_2 = d_1 - \sigma\sqrt{T}.$$

We then compare the performance of these strategies based on the simulated stock option prices; the results are summarized in Table 4. It is noteworthy that, except for the straddle-sale strategy for TSMC and the 1:2 hedging sale strategy for Fubon, the proposed trading strategies for both stocks beat the buy-and-hold strategy. Although the proposed strategies do not uniformly dominate the buy-and-hold strategy in all regimes, it is fair to say that the trading strategies developed here compare favorably with it.

4 Conclusions

Trading rules involving derivatives, such as the straddle-strategy and the 1:2 hedging strategy, have been widely applied by practitioners. But, only if investors can correctly foresee the change points between stable and turbulent regimes in future stock prices, can these strategies perform well. To the best of the authors' knowledge, to date there have been no suitable econometric models to do so. In this paper, we employ the IRS model to capture

Table 4: Comparison of the average DRRs of the trading strategies based on the simulated option prices.

	TSMC			Fubon		
Trading Rules	Whole Period	Turbulent	Stable	Whole Period	Turbulent	Stable
Straddle:	1.973%	–	–	0.721%	–	–
Purchase (+**C**+**P**)	–	4.402%	–	–	0.771%	–
Sale (−**C**−**P**)	–	–	−1.375%	–	–	0.653%
1:2 hedging:	1.051%	–	–	0.269%	–	–
Purchase (−**S**+**2C**)	–	0.581%	–	–	0.735%	–
Sale (+**S**−**2C**)	–	–	0.021%	–	–	0.049%
Buy-and-hold:	0.135%	0.261%	−0.251%	0.123%	−0.063%	0.201%

Note: Same as Table 3.

different dynamic patterns and to predict the change points between these regimes in Taiwan's stock market. Several interesting results emerge. Firstly, we find that random-walk nonstationarity is likely to be the prevailing dynamic pattern in more than 60 percent of the sample periods, whereas stationarity and stable regimes are likely to prevail in the remaining periods. Movements in the prices of the two stocks can thus be classified on the basis of the timing of stable and turbulent regimes. This is in sharp contrast to earlier findings in the literature, cf. Samuelson (1965) and Summers (1986). Secondly, the empirical applications to TSMC and Fubon stock prices suggest that making the distinction between stable and turbulent regimes provides valuable information vis-à-vis the stock market. In particular, we find that, based on our simulation results, profitable strategies can be determined. Compared with the buy-and-hold strategy, these profitable strategies can lead to higher returns even when transaction costs are taken into account.

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