ชื่อเรื่อง **แบบจำลองการเปลี่ยนแปลงตามภาวะที่สังเกตได้ของผลตอบแทนการลงทุนในตลาดหลักทรัพย์แห่งประเทศไทย**

Title **Observable Regime-switching Models for SET Returns**

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บทคัดย่อ

การศึกษานี้สำรวจการเปลี่ยนแปลงสภาวการณ์ในตลาดหลักทรัพย์แห่งประเทศไทย โดยใช้แบบจำลองการเปลี่ยนแปลงตามภาวะที่สังเกตได้ (Observable regime-switching model) ชนิดหนึ่ง คือ แบบจำลองอัตสหสัมพันธ์ที่มีค่าแบ่งแยกกลุ่มตัวอย่าง (Threshold Autoregressive model) กับข้อมูลผลตอบแทนการลงทุนในตลาดหลักทรัพย์แห่งประเทศไทย ในช่วงปี พ.ศ. 2548-2550 โดยใช้ข้อมูลการหมุนเวียนการซื้อขายเป็นตัวบ่งชี้สภาวการณ์ ผู้ศึกษาพบว่าสภาวการณ์ในตลาดหลักทรัพย์แห่งประเทศไทยสามารถแบ่งได้เป็น 2 ประเภท ได้แก่ 1) ภาวะปกติ ซึ่งผลตอบแทนเฉลี่ยของการลงทุนเป็นบวก และมีระดับการหมุนเวียนการซื้อขายไม่สูง 2) ภาวะซบเซา (Bear market) ซึ่งผลตอบแทนเฉลี่ยของการลงทุนเป็นลบ และมีระดับการหมุนเวียนการซื้อขายสูง ผู้ศึกษาพบอีกว่าแบบจำลองข้างต้นเป็นแบบจำลองเชิงพรรณนาที่ดีกว่าแบบจำลองอัตสหสัมพันธ์อันดับที่ 1 (AR(1)) นอกจากนั้น การประเมินประสิทธิภาพการพยากรณ์นอกกลุ่มตัวอย่าง (Out of sample) ในช่วงปี พ.ศ. 2551 แสดงให้เห็นว่า แบบจำลองอัตสหสัมพันธ์ที่มีค่าแบ่งแยกกลุ่มตัวอย่าง และแบบจำลองอัตสหสัมพันธ์ มีความสามารถในการพยากรณ์ค่อนข้างเท่าเทียมกัน ในส่วนสุดท้าย ผู้ศึกษาได้เสนอประเด็นที่เกี่ยวข้องกับการพัฒนาแบบจำลองการเปลี่ยนแปลงตามภาวะที่สังเกตได้

คำสำคัญ: แบบจำลองการเปลี่ยนแปลงตามภาวะที่สังเกตได้ แบบจำลองอัตสหสัมพันธ์ที่มีค่าแบ่งแยกกลุ่มตัวอย่าง ตลาดหลักทรัพย์แห่งประเทศไทย

Abstract

This paper investigates regime shifts in the Stock Exchange of Thailand (SET) using observable regime-switching models. Threshold Autoregressive (TAR) models with a regime indicator being turnover data are applied to SET returns in the 2005-2007 time period. It is found that the market returns can be characterised by two regimes: (i) the normal regime, associated with positive mean returns and lower turnover; (ii) the bear regime, associated with negative mean returns and high turnover. As a descriptive model, the TAR models are better than a simpler AR(1) model. In addition, forecasts for the 2008 period are produced in order to evaluate out-of-sample performance of the models. Forecastability of the TAR models, however, is about the same level as that of the AR. Finally, the paper suggests aspects of the TAR model which can be further developed.

Key words: Observable regime-switching model; Threshold Autoregressive model; the Stock Exchange of Thailand.

Introduction

Stock markets, like other financial markets, are prone to booms – and to busts. If such periods form distinct *regimes* of which observations in time series may be generated by different mechanisms, the usual linear modelling techniques will be inadequate in representing the market conditions underlying prices and returns. Knowledge of the regimes provides important information that could influence portfolio selection strategies, particularly on predictability of asset returns.

Asset pricing theory suggests that market frictions such as liquidity (or the lack thereof) should help justify the predictability of asset returns (Campbell et al., 1997). Loosely speaking, liquidity is the 'ease of trading a security' (Amihud et al., 2005: 2). Trading volume is hence a prime, and in fact standard, proxy for liquidity in the literature. As Cochrane (2004: 11) posits, it is 'well-known' that equity price indices and trading volume are significantly correlated. Studies on the Stock Exchange of Thailand (SET), in addition, support the modelling of returns and trading volume jointly (Ohrukpaisal, 2003; Chiradatesakunvong, 2004). One approach to tackle this problem is to use the trading volume as an observable variable determining regimes.

Observable regime-switching (RS) models can be considered as a combination of regression and time series analyses – of which the exogenous 'regime variable' does not enter directly into the time-series equation – and are alternative to the more complicated unobservable RS models.[1] The *Threshold Autoregressive* (TAR) model is an appropriate choice of RS models, when there is a single regime variable, herein the trading volume.

The intention of the present research is to explore the existence of regimes and nonlinearity in returns on the SET. The organisation of the paper is as follows. The next section reviews the TAR model, its estimation, and threshold selection issues. Section 3 describes data and the methodology employed in the study. Section 4 presents and discusses the results, with some consideration on forecastability of the TAR model. The paper ends with the conclusions and suggestions for further research.

TAR Model

The non-linear TAR model, initially proposed by Tong (1978), splits the time series of interest into subsets, or 'regimes' defined with respect to the value of some regime indicator. Application of TAR models in financial markets is not uncommon, for example, to stock returns (Li and Lam, 1995), to exchange rate changes (Alba and Park, 2005) and to property returns (Lizieri et al., 1998). Further discussion of different RS models can be found in Tong (1990); Franses and van Dijk (2000) provide an excellent textbook treatment on the subject.

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[1] Unobservable RS models often formulate the regime as a Markov (hidden) process. This type of model is due to Hamilton (1989, 1992); recent studies include Ang and Bekaert (2002) and Guidolin and Timmermann (2007), and particularly for SET returns, Chusil (2003).

Based on a conventional linear time-series model (i.e. ARMA-type models) – assuming without loss of generality that asset returns follow an AR(1) process in both regimes – a generic two-regime TAR model is given below.

$$r_t = \begin{cases} \alpha_1 + \phi_1 r_{t-1} + \varepsilon_t & \text{if } d_t \le c, \\ \alpha_2 + \phi_2 r_{t-1} + \varepsilon_t & \text{if } d_t > c, \end{cases} \tag{1}$$

where r_t is the asset returns, d_t a regime indicator, and c the predetermined threshold level. The level c divides the sample into two groups with different parameter values. In a classical study of structural break in which d_t is the time index, c represents the break time, say, the date that the break occurs. If d_t represents other variable than time, we in effect define break points, and the corresponding regimes, on other domain than chronological order.

There is a large number of plausible specifications of the TAR model. As a standard procedure in time-series econometrics, the AR(1) specification can be generalised to AR(p). Moreover, the assumed structure in each regime might differ. Model selection also concerns the regime indicator d_t which can be chosen on grounds of both theory and empirics. In practice, the "true" threshold variable is of course 'unknown', and an important question is how it can be determined (Franses and van Dijk, 2000: 87). One particular case is when a lagged value of r_t, r_{t-k} where $k \in \{1, 2, ..., t-1\}$, is used as the regime variable, hence the name *Self-exciting TAR* or SETAR model.[2] Finally, extension to models with more than two regimes is straightforward, although this will result in specification becoming much more complicated – for m regimes we have to determine $m-1$ threshold values.

We shall then consider estimation of the TAR model. When the threshold level is fixed, the equation (1) is linear in the remaining parameters, and can thus be easily estimated by OLS. This can be seen by rewriting (1) more compactly as

$$r_t = \theta_1' \mathbf{x}_t (1 - I[d_t > c]) + \theta_2' \mathbf{x}_t I[d_t > c] + \varepsilon_t, \tag{2}$$

where $\theta_j = (\alpha_j, \phi_j)'$ with $j \in \{1, 2\}$, $\mathbf{x}_t = (1, r_{t-1})'$, and $I[\cdot]$ is an indicator function which takes the value of 1 if the condition is satisfied and 0 otherwise. The OLS formula is given by

$$\hat{\theta}(c) = \left(\sum_{t=1}^{n} \mathbf{x}_t(c) \mathbf{x}_t'(c) \right)^{-1} \left(\sum_{t=1}^{n} \mathbf{x}_t(c) r_t \right), \tag{3}$$

where $\mathbf{x}_t(c) = [\mathbf{x}_t'(1 - I[d_t > c]), \mathbf{x}_t' I[d_t > c]]'$, as well as the estimators $\hat{\theta}(c) = (\theta_1', \theta_2')'$, is now conditional on c. Under the classical assumptions,

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[2] The SETAR model might be a good alternative when an exogenous regime indicator is not readily available.

$$Var(\hat{\theta}(c)) = \sigma^2 \left(\sum_{t=1}^{n} \mathbf{x}_t(c)\mathbf{x}_t'(c) \right)^{-1}. \tag{4}$$

$Var(\hat{\theta}(c))$ can be estimated by replacing the true variance by its estimate $\hat{\sigma}^2(c) = \frac{1}{n}\sum_{t=1}^{n}\hat{\varepsilon}_t^2(c)$, which is computed from the (conditional) residuals $\hat{\varepsilon}_t(c) = r_t - \hat{\theta}'(c)\mathbf{x}_t(c)$. It is worth noting that OLS is consistent, and gives estimates which are asymptotically normally distributed.

The next step concerns the estimation of the threshold level. We can define the empirical threshold level $\hat{c}$ at the value which yields the lowest possible standard error of regression (Franses and van Dijk, 2000); i.e.,

$$\hat{c} = \underset{c \in C}{\operatorname{argmin}}\, \hat{\sigma}(c), \tag{5}$$

where C denotes the set of all allowable threshold values. As a concluding remark, it is worth noting that C should be constructed such that each regime contains enough observations in order that OLS produce reliable estimates. A popular choice of C is to require that each regime contain at least 15% of the number of observations (Franses and van Dijk, 2000: 84).

Data and Methodology

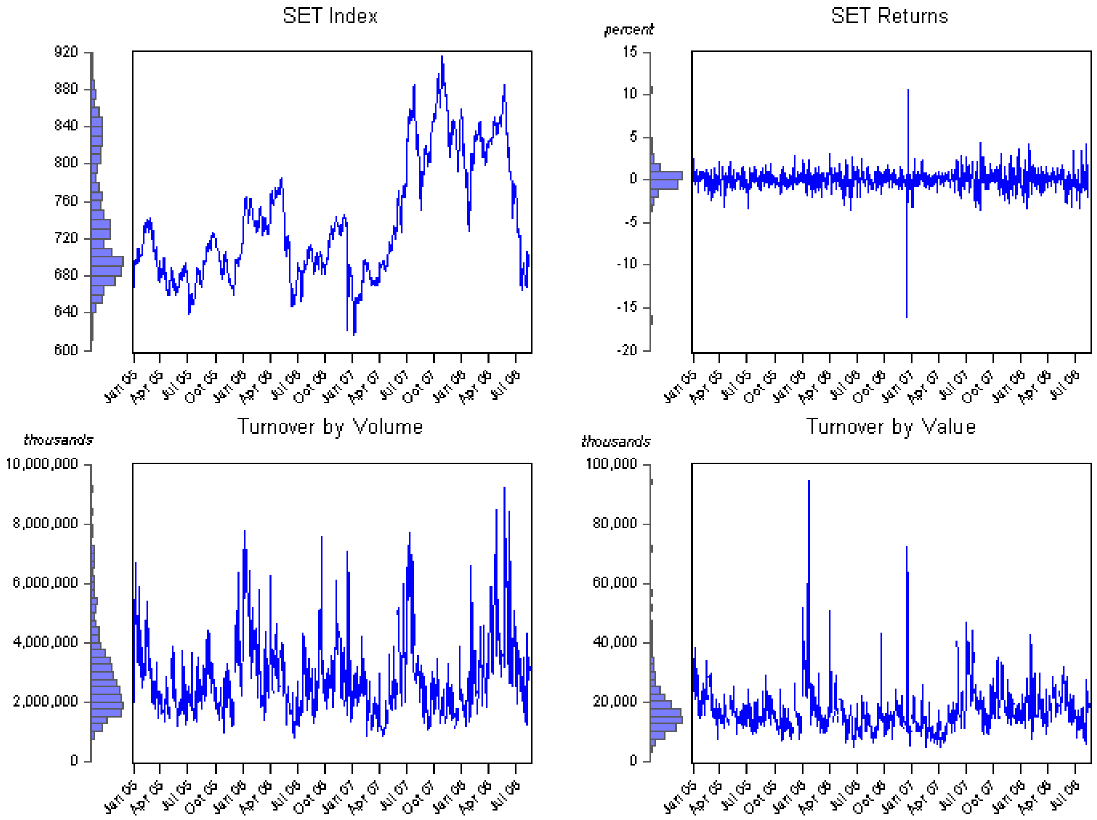
1. Data Description

The study is conducted on the SET Index (hereafter SETI) because of two main reasons. As a standard practice in the literature, market indices can be used as a measure of aggregate market movements, and to represent overall performance of the market. Furthermore, by using market indices, a researcher makes attrition, survivorship bias, and thin trading of individual stocks irrelevant.

The daily data for the SETI and the corresponding turnover figures – namely VO (turnover by volume) and VA (turnover by value) – are obtained from Thomson Financial Datastream. The SETI is a composite price index calculated from the prices of all common stocks on the main board, and is market capitalisation weighted. VO is the total number of constituent shares traded on the SET on a particular day, while VA shows the aggregation of the number of shares traded multiplied by the closing price for each stock. The daily market returns (hereafter RET) are computed as a continuously compounded rate of change in SETI. In order to create a workable series of daily returns, following Beran and Ocker (2001), missing values on non-trading days in the SETI are ignored. Each observation in the returns series is, in effect, a change from the last trading day; the series is then treated as equidistant.

Three years of daily observations from January 2005 to December 2007 (781 observations) are used in the estimation, and the data for year 2008 (162 observations) are kept for forecasting performance evaluation; all trading days are included. The sampling period is chosen such that the start date does not go too far into the past, still providing enough observations for the estimation purpose.[3] No special treatment has been made to the unusually low and high returns of 19 and 20 December 2006, which arguably result from the Bank of Thailand's policy announcement on 'Reserve Requirement on Short-Term Capital Inflows' (Bank of Thailand, 2006). The reason for such practicing is that this type of regulation change is actually not unusual in financial markets. The time-series plots of the data, along with the histograms, are shown in figure 1. Both VO and VA are positively skewed; in other words, they have a long tail of higher values.

Figure 1: SET Data



Source: Thomson Financial Datastream

2. Model Specification, Estimation, and Testing

Granger (1993) strongly recommends a specific-to-general approach to model specification of non-linear time series models. We shall thus proceed the specification search by starting from an AR(1) model, applying diagnostic tests to check for model adequacy, and then including additional lags if necessary.[4] It is assumed that model specification does not vary across regimes.[5]

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[3] As noted by Alexander (2001), one should use several years of daily data, sufficient to provide stable parameter estimates, but not too many that the estimates do not reflect changes in market conditions.

[4] It is generally accepted that the adequacy of time-series modes could be established through examination of a correlogram of the residuals (Tsay, 2005).

[5] As will be shown later, this point is, however, confirmed by the empirical evidence.

Model estimation has already been discussed in section 2. Further algorithm to obtain $\hat{c}$ as in (5) will be further explained here. A *grid search*, which is particularly appropriate for a one-dimensional problem, is chosen as the numerical optimisation algorithm.[6] The standard errors of regression are computed at 101 equally spaced points, $c_0, c_1, \ldots, c_{100}$, over the range of the trading volume (the difference between the maximum VO and the minimum VO). The same procedure applies to VA. Some of the regressions are not estimable due to singularity of the $\mathbf{x}_t(c)$. Finer grid searches are then conducted to identify the global minimum, although multiple minima are expected because of the discreteness of the data.

The evaluation of the TAR model against its AR counterpart is conducted by comparing their in-sample goodness of fits. The reason for this is that statistical tests with the null hypothesis of equal parameter values across regimes suffer from the problem of *unidentified nuisance parameters*.[7] Forecasting evaluation is also conducted to help justify the merits of the TAR model.

Results and Discussion

1. Preliminary Analyses

The Augmented Dickey-Fuller (Unit Root) test strongly rejects the null hypothesis that RET has a unit root, so non-stationarity is not a matter of concern. In addition, the correlogram of RET suggests AR(1) an appropriate model for the mean returns. The Box-Ljung test, with inclusion up to 20 lags (about a month's time), indicates no significant correlation in the residuals from the AR(1) specification of RET.[8] Since the adequacy of the model has been already obtained, AR(1) is therefore the best specification for SET as implied by the specific-to-general principle.

2. Estimated TAR Models

Figure 2 shows the s.e.'s of regressions using different threshold values. Subsequent finer searches indicate that, for this data set, the threshold turnover volume ($\hat{c}_{VO}$) is 7,027,520 thousand shares, and the threshold turnover value ($\hat{c}_{VA}$) is 55,218 thousand baht.

The estimated TAR models using VO and VA as a regime variable are reported in box 1 below, together with the estimated AR(1) for comparison. Both of the TAR models yield similar results; all of their estimated coefficients have same signs, and are close in magnitude.

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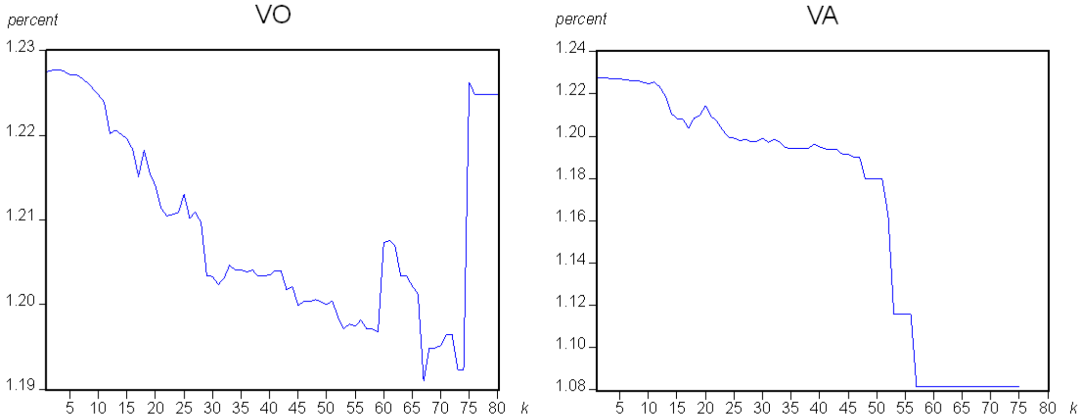
[6] See Harvey (1990: 124).

[7] See Franses and van Dijk (2000: 100).

[8] The Box-Ljung test, however, detects correlation in the squared residuals, suggesting the presence of Autoregressive Conditional Heteroscedasticity (ARCH) effects. Nevertheless, since modelling volatility in SET returns is not central to the present study, such effects are not examined further.

Figure 2: First Grid Searching Result



Notes: (i) the x-axis shows the points of the equally spaced intervals; i.e. the number k refers to the k-th threshold value, c_k ; (ii) missing observations are due to singularity of the regression.

Box 1: Estimation Result

- *TAR using Turnover by Volume* (TAR-VO)

$$RET_t = \begin{cases} \underset{\substack{(0.042)\\[0.223]}}{0.050} - \underset{\substack{(0.034)\\[0.000]}}{0.116}\, RET_{t-1} & \text{if } VO_t \le \hat{c}_{VO} \\ -\underset{\substack{(0.510)\\[0.000]}}{4.059} + \underset{\substack{(0.448)\\[0.000]}}{3.884}\, RET_{t-1} & \text{if } VO_t > \hat{c}_{VO} \end{cases} \tag{6}$$

$$R^2 = 0.114 \quad \text{s.e.} = 1.162 \quad \text{BIC} = 3.166 \quad n_1 = 773 \quad n_2 = 8$$

- *TAR using Turnover by Value* (TAR-VA)

$$RET_t = \begin{cases} \underset{\substack{(0.039)\\[0.149]}}{0.056} - \underset{\substack{(0.031)\\[0.000]}}{0.110}\, RET_{t-1} & \text{if } VA_t \le \hat{c}_{VA} \\ -\underset{\substack{(0.814)\\[0.000]}}{4.869} + \underset{\substack{(1.333)\\[0.000]}}{14.304}\, RET_{t-1} & \text{if } VA_t > \hat{c}_{VA} \end{cases} \tag{7}$$

$$R^2 = 0.232 \quad \text{s.e.} = 1.081 \quad \text{BIC} = 3.024 \quad n_1 = 779 \quad n_2 = 2$$

- *AR*

$$RET_t = \underset{\substack{(0.044)\\[0.422]}}{0.035} - \underset{\substack{(0.036)\\[0.006]}}{0.099}\, RET_{t-1} \tag{8}$$

$$R^2 = 0.009 \quad \text{s.e.} = 1.226 \quad \text{BIC} = 3.260$$

Notes: (i) s.d.'s are reported in parentheses (.), and p-values in brackets [.]; (ii) n_i is the number of observations in regime i .

Distinctive behaviour emerges between the two regimes. The first regime, associated with lower turnover, can be interpreted as a ‘normal’ state of the SET. The (unconditional) mean returns in this regime are equal to 11.20% and 15.54% per annual (approximately 250 trading days) for the TAR-VO and TAR-VA respectively. Although the estimated (mean) returns process is barely persistent with the lag coefficient of about 0.1 (far less than 0.5), the estimates are highly significant. This finding implies the presence of market frictions and inefficiency, which are consistent with prior studies on the SET (e.g. Mun and Kee, 1994; Khanthavit (ed.), 2003; Chancharoenchai et al., 2005). In the second ‘bear’ regime, associated with high turnover and negative conditional mean returns, RET is an explosive nonstationary process. The result for this regime could be attributed to concerted selling pressure in the SET during such a period.[9]

The TAR models also exhibit slightly higher persistence in the returns process, compared with the AR model. More importantly, they achieve much better goodness of fit than AR does, according to both R^2 and the Bayesian (Schwarz) Information Criterion. This is not completely unexpected – with no distinction between states, the AR model includes the unusual observations in its regression while these are basically captured by the regime indicator (a dummy variable) of the TAR models. TAR-VA yields even better fit than TAR-VO. This is probably because VA contains more information than VO; while the latter is merely the number of shares, the former is like the “weighted’ number of shares. To illustrate, suppose that stocks A and B have the same trading volume on a particular day; the stock with higher price will have more contribution to the overall market movement.

Cross-validation is conducted by further dividing the estimation period into three sub-samples (2005, 2006, and 2007), each of which contains one year of observations. Similar results are obtained.[10] This could ensure that the results in (6) and (7) are actually a consequence of regime shifts, and not an artifact of *data mining*.[11] It is thus concluded that regime shifts are actually phenomena of returns on the SET, where at least two regimes are found.

3. Forecasting Evaluation

Although the focus of the paper is on the existence of regime in SET returns, forecasting is also of interest, especially in practical application. Static one-period forecasts for the year 2008 data are produced using the three models. The forecasting TAR-VO model is shown below (the one for TAR-VA shares the same formulation). It is assumed that at time $t+1$ it is known for certain in which regime RET is; in other words, we abstract from uncertainty of VO_{t+1}.

$$\overline{RET}_{t+1} = \begin{cases} 0.050 - 0.116RET_t & \text{if } VO_{t+1} \le \hat{c}_{VO} \\ -4.059 + 3.884RET_t & \text{if } VO_{t+1} > \hat{c}_{VO} \end{cases} \tag{9}$$

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[9] Care must be taken, though, in interpreting the second regime’s result because of the small number of observations available for the estimation.

[10] See the appendix.

[11] See Nelson (2004: 40, 44).

During 2008, as for the TAR-VO model only two observations are in the second regime, while RET stays in the normal regime all the time in the TAR-VA model. As a result, all of the three models produce close forecast values. In contrast to the in-sample performance, however, the TAR models do not seem to unarguably surpass the simpler AR model.[12] According to a traditional RMSE criterion (see table 1), the AR model's performance is actually between than that of the two TAR models. Nevertheless, the correlation between TAR-VO forecasts and the actual RET is higher than that between AR forecasts and RET. Such correlation gives some information on the predictability of the SET returns, which is useful in forming portfolio strategies. This result implies that it might actually be desirable to incorporate regime shifts in the econometric model of SET returns.

Table 1: Out-of-sample Performance

Model	*TAR-VO*	*TAR-VA*	*AR*
RMSE	1.637	1.369	1.364
Corr.	0.060	0.021	0.021

Note: Corr. refers to the correlation (in absolute value) between the actual RET and the forecast values.

Conclusions and Suggestions

It is argued that there may exist different regimes in the SET depending on the level of the market's trading volume. Two TAR models have been presented, both of which are significant in modelling SET returns. The fact that two highly distinct regimes emerge suggests, in addition, that the conventional linear time-series models might be subject to misspecification error. The results of the study also confirm the contention that turnover plays a significant role as a regime indicator.

Using SET returns data, the empirical results do support the TAR models (both TAR-VO and TAR-VA) as a suitable replacement for a single-regime AR model in many aspects. First, the TAR models are capable of extracting a "unique" threshold level of the regime variables, the strong evidence in favour of regime shifts in the SET. As a descriptive model, traditional goodness-of-fit measures support the superiority of the TAR models. From a forecasting point of view, however, the TAR models perform at about the same level as the AR does. Even so, they show some potential to be a better forecasting model, especially when predictability of asset returns is concerned.

The TAR models are certainly not without flaws. Several issues need to be addressed in order to better the performance of the TAR models. For one thing, we need to take into account the ARCH effects found in RET. It is worth stressing that incorporating ARCH would in theory increase efficiency of

[12] As studied in Dacco and Satchell (1999), the bad forecastability of TAR models can be reasonably expected. However, the relatively unsatisfactory forecasting performance of the TAR models could have also resulted from the poor estimation of the bear regime's coefficients. Recall that the number of observations in this regime accounts for less than 1% of the total observations.

OLS estimator. There is also a possibility of regime shifts in volatility as well.[13] To the best of the author's knowledge, no research has been conducted on observable RS models in both the mean returns and volatility. For another thing, in the TAR formulation the turnover data have been treated as exogenous. Both prices and quantities are in fact endogenous in most economic models. Bivariate models of returns and turnover are therefore more desirable. Generalisation of the univariate TAR model to the multivariate framework is straightforward, at least conceptually.[14]

Acknowledgement

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Appendix

The results for TAR-VO sub-samples 2006 and 2007, and TAR-VA sub-sample 2006 are reported in equations (10), (11), and (12) in order below. Most of the coefficients have the same sign, and are close in magnitude to those in (6) and (7). Estimation for the sub-sample 2005 and TAR-VA sub-sample 2007 yields a single-regime regression, and hence the results are omitted.

- *TAR-VO*

$$RET_t = \begin{cases} \underset{\substack{(0.077) \\ [0.699]}}{0.029} - \underset{\substack{(0.049) \\ [0.000]}}{0.301} RET_{t-1} & \text{if } VO_t \le \hat{c}_{VO} \\ -\underset{\substack{(0.627) \\ [0.000]}}{6.182} + \underset{\substack{(0.533) \\ [0.000]}}{5.173} RET_{t-1} & \text{if } VO_t > \hat{c}_{VO} \end{cases} \tag{10}$$

$$R^2 = 0.379 \quad \text{s.e.} = 1.221 \quad \text{BIC} = 3.307 \quad n_1 = 254 \quad n_2 = 6$$

$$RET_t = \begin{cases} \underset{\substack{(0.074) \\ [0.344]}}{0.070} + \underset{\substack{(0.062) \\ [0.241]}}{0.073} RET_{t-1} & \text{if } VO_t \le \hat{c}_{VO} \\ \underset{\substack{(1.009) \\ [0.080]}}{1.773} - \underset{\substack{(0.993) \\ [0.944]}}{0.069} RET_{t-1} & \text{if } VO_t > \hat{c}_{VO} \end{cases} \tag{11}$$

$$R^2 = 0.020 \quad \text{s.e.} = 1.189 \quad \text{BIC} = 3.254 \quad n_1 = 259 \quad n_2 = 2$$

Notes: (i) s.d.'s are reported in parentheses (.), and p-values in brackets [.]; (ii) n_i is the number of observations in regime i.

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[13] Modelling regime shifts in volatility might be done using the Threshold GARCH model (Engle and Patton, 2007).

[14] In this setting, the threshold variable can then take a form of a linear combination of the two series (Tsay, 1998).

- *TAR-VA*

$$RET_t = \begin{cases} \underset{\substack{(0.068) \\ [0.579]}}{0.038} - \underset{\substack{(0.044) \\ [0.000]}}{0.291} RET_{t-1} & \text{if } VA_t \le \hat{c}_{VA} \\ -\underset{\substack{(0.820) \\ [0.000]}}{4.869} + \underset{\substack{(1.344) \\ [0.000]}}{14.304} RET_{t-1} & \text{if } VA_t > \hat{c}_{VA} \end{cases} \tag{12}$$

$$R^2 = 0.505 \quad \text{s.e.} = 1.089 \quad \text{BIC} = 3.080 \quad n_1 = 259 \quad n_2 = 2$$

Notes: (i) s.d.'s are reported in parentheses (.), and p-values in brackets [.]; (ii) n_i is the number of observations in regime i.

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