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THREE ESSAYS ON THE SECURITIES EXCHANGE OF THAILAND

by

PORAMETEE VIMOLSIRI, B.A., M.I.A.

A thesis submitted to
the Faculty of Graduate Studies and Research
in partial fulfilment of
the requirements for the degree of

Doctor of Philosophy

Department of Economics

Carleton University

Ottawa, Ontario

17 May, 1994.

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submitted by

Poramettee Vimolsiri, B.A., M.I.A.

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Chair, Department of Economics

Thesis Supervisor

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Abstract

The thesis contains three essays entitled; "Tax News and the Securities Exchange of Thailand", "Simple Trading Rules, Profit, and the Stochastic Properties of Stock Returns in Thailand", and "The Relationship between Daily Returns, Volatility, and Trade Volume in the Markov Switching Model of Stock Returns". All three consist of empirical research that addresses various issues relating to the workings of the stock market in Thailand.

An event study in the first essay examines the reaction of stock prices to the major sales tax reform which took place in Thailand on January 1st, 1992. The results from 31 industrial portfolios and 187 individual stocks demonstrate that this event did not generate significant abnormal returns and that the reaction of stock prices did not clearly conform to the predicted cross-sectional economic effects of the reform.

In the second essay, the simulation of simple trading rules shows that they generate statistically as well as economically significant profits. In addition to this being an evidence of stock market inefficiency, the profits from some trading rules show a characteristic which contradicts the mean-variance relationship described in the conventional asset-pricing model. The bootstrap simulation confirms that these trading rule profits cannot be satisfactorily explained by various stock return-generating models in the existing literature.

The final essay is the first to study the empirical relationship between daily stock returns and trading volume in a multivariate Markov switching model. The estimation reveals that the stock returns in Thailand are driven by a switching process

between two regimes representing the high-variance and low-variance states of the stock market. Furthermore, the Markov switching model yields many interesting results regarding the relationships between contemporaneous or lag volume and expected returns, as well as some new insights on the influence of trading volume on transitional probabilities between the stock market states.

To my parents, Mr. Putra and Mrs. Sumon Vimolsiri.

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Introduction

This thesis contains three essays on the stock market in Thailand. All three consist of empirical research that addresses various issues relating to the workings of the stock market. The emphasis is on the nature of stock pricing and the characteristics of stock returns. The aim of the thesis is to increase understanding of how an emerging stock market, such as that in Thailand, has performed relative to theories that guide economists in thinking about stock markets. This aim is accomplished by using current research tools, which have proven to yield many interesting insights into the workings of advanced stock markets. The three essays, taken together, apply both standard methodologies and those on the frontier of financial economic research to the data from the Securities Exchange of Thailand (SET). The data from the SET have rarely been used, in comparison with data from more advanced stock markets, thus there are genuine opportunities to test the robustness of previous findings that use data from advanced stock markets, as well as opportunities to discover new findings. With respect to the techniques and issues that these essays employ and address, it is likely that this thesis is the pioneer in applying them to the stock market in Thailand. Apart from the universal benefit this thesis provides, namely, the contribution to the existing literature of further empirical evidence derived from a new and relatively less-known stock market, it is also hoped that this venture will generate enthusiasm leading to more active research using the stock market in Thailand, since such research still lags behind the market's popularity and its increasingly important status within Thailand's financial system.

The first essay in this thesis is entitled "Tax News and the Securities Exchange of Thailand." It examines the reaction of stock prices to news about a change in public policy, in this case a major tax reform. The reform of the indirect taxation system in Thailand replaced the cascade-type manufacturers' tax by a consumption-type value added tax (VAT) on January 1st, 1992. The rationale for this change was based on the tax's contribution to economic efficiency. However, the comprehensive changes resulting from this tax reform can cause differential effects on different industries, as predicted by studies from both public and private sectors. The stock market event-study method is applied to this episode of tax reform and the Securities Exchange of Thailand (SET) in order to compare the reaction in the stock market with the predicted cross-sectional economic effects of the reform.

The results demonstrate that abnormal returns from 31 industrial portfolios and 187 individual stocks are not significant and do not clearly conform to predictions. Since the test relies on the joint-hypothesis regarding tax effects and the efficiency of the stock market, these results may have two important interpretations. The cross-sectional effects may not be the most significant aspect of this tax reform, or the SET may be inefficient. The former interpretation contradicts the widely held opinion about broad-based consumption tax reform and questions how to assess appropriately its potential effects on the economy. The latter interpretation challenges the adequacy of the conventional economic model, which ascribes a close link between tax changes and stock market reaction based on the Efficient Stock Market theory. Each interpretation is an important lesson for the practitioners and the theorists of public

finance and financial economics, and thus they invite more research into this area.

The second essay, "Simple Trading Rules, Profit, and the Stochastic Properties of Stock Returns in Thailand," evaluates the SET performance in accordance with one concept of stock market efficiency and examines the stochastic properties of stock returns in this market. Simulation of trading rules is used as a research tool to facilitate these two goals. The information set upon which this essay bases its concept of stock market efficiency consists of current and past stock prices. In the definition given in Jensen (1978), if the stock market is efficient with respect to a certain information set then there must be no dynamic trading rules based on this information set which can generate an economically significant profit higher than the profits generated by the buy-and-hold strategy. There are now numerous findings in the industrial economies that stock markets are not efficient with respect to various definitions.

The debate over stock market efficiency and inefficiency has stimulated recent interest in the re-examination of trading rules, which have always been popular among professional stock market investors. There are two distinct uses of trading rules, according to the literature. Earlier studies of trading rules focus mainly on the economic significance of profit in order to test the efficiency of the stock market. Recently, Brock, Lakonishok, and LeBaron (1992) demonstrated that combining trading rule simulation with the bootstrap technique provides important information regarding the stochastic properties that are useful for the dynamic modelling of the stock returns process.

This essay uses both aspects of trading rule simulation to study the performance and the empirical features of Thai stock market. The result is evidence that trading rules generate statistically as well as economically significant profits. In addition, interesting stochastic properties of returns, which have been found by trading rule simulation in the U.S. stock market, are also found in the Thai market. The buy signals generated from trading rules identify a group of returns with high mean and low variance, while a group of returns under sell signals yields low mean and high variance. These characteristics of returns are interesting since they provide an empirical contradiction to the asset pricing theory, which associates high returns with high risk. In the bootstrap simulation, the trading rule profits cannot be explained by a stock return-generating model such as a random walk with a drift, or by the Markov-chain, which imposes states ex ante. The AR(1) model has the potential to explain some qualitative aspects of the profit. These results imply that, firstly, stock markets may not be efficient and, secondly, trading rules can capture special characteristics of stock returns unexplainable by many common stock return models.

The final essay, "The Relationship between Daily Returns, Volatility, and Trade Volume in the Markov Switching Model of Stock Returns," further pursues the issue related to the stochastic properties of stock returns in the SET by using the Markov switching regression framework. The economic issue under investigation is the relationship between stock returns and trading volume. An increasing number of recent theoretical models postulate an important role for trading volume in pricing stocks. These models illustrate that the relationship between stock returns and trading

volume is a complicated one. In many cases, the predicted relations differ between models or within the model, depending on the mechanism that generates stock trading. At this stage, these theoretical models are difficult to test directly with data, owing to their strict assumptions, which cannot easily be translated into an empirical testing design. However, an empirical relationship is needed to guide and confront this theoretical pursuit. Various empirical studies have shown that more can be learned about the dynamic properties of stock returns by studying them jointly with the behaviour of trading volume.

This essay extends the existing literature on the empirical relationship between trading volume and daily stock returns into the Markov switching framework, which can be used to explore various nonstationary structures in a stock return series and their relationship to other economic variables. Specifically, two questions are raised. Firstly, is there any connection between daily returns, volatility, and trading volume if stock returns follow a Markov switching process? Secondly, how does trading volume affect transitional probabilities, if it is allowed to influence the transitional probabilities of the Markov process? Many interesting results arise out of the estimation. Firstly, in the context of the two-state Markov switching model, stock returns in Thailand are driven by a switching process between two regimes representing the high-variance and low-variance states of the stock market. Secondly, contemporaneous volume is positively related to returns, with its effect on expected returns higher in the high-variance state. Thirdly, the lag volume is positively related to the current-period expected returns. Increases of one standard deviation in lag

volume can increase one-third the size of expected returns. Fourthly, contemporaneous volumes have a significant but opposite effect on the persistence probabilities of the two regimes. Increases in volume decrease the chance that a low-variance state will continue but increase the chance that a high-variance state will be prolonged. The lag volume has some statistically weak effects on transitional probabilities. Lastly, unlike many other modelling experiences in the literature, the Markov switching model can capture these interesting relationships using fast-moving measures of volume such as the daily growth rate.

These three essays, although few in number, have produced some interesting results. Furthermore, the collection deals with issues that reflect the fact that the workings of the stock market are one of the prime concerns of people in various professions, from academics and investors to public policy makers. Despite the different objectives that guide individual parties in their involvement with a stock market, it is believed that all can benefit from the insights of rigorous academic research.

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I: Tax News and Securities Exchange of Thailand

Tax News and the Securities Exchange of Thailand

I. Introduction

An important change in Thailand's tax system took place on January 1st, 1992, when the old manufacturing sales tax, which had been in place since 1961, was replaced by the value added tax. This tax reform represents a significant change in the structure of indirect taxation, which is the main source of government revenue. The move towards using a value added tax as an instrument for levying broad-based consumption taxes is not restricted to Thailand but is the common direction being taken by tax reforms the world over. In 1950 no countries imposed a value added tax; by 1986, less than 40 years later, over 60 countries, 40 of which are classified as developing economies by the World Bank, had implemented some form of value added tax.¹ Harberger (1990) states that, "No public finance development of the last half century can rival the emergence and spread of the value added tax." Recent trends also show that an increasing number of developing economies have implemented or propose to implement a value added tax system. Greece did so in 1987, Hungary and the Philippines in 1988 and South Africa in 1989.² Since the value added tax generally is a broad-based tax system, introducing it into an economy has the potential to generate various effects; therefore, news about this type of tax reform is followed keenly by businessmen and investors.

¹ *Value Added Taxation in Developing Countries*, 219.

² See Tait (1988) Tables 1-2, pp. 10-14, for a more complete list.

The rationale given for adopting the value added tax system in Thailand, as expressed by academics and fiscal planners, is that it contributes to economic efficiency, which will benefit the Thai economy as a whole. However, comprehensive changes of the indirect tax system resulting from this tax reform can have different effects on different industries. Some industries will benefit while some will suffer losses as a result of these tax changes.

This aspect of tax reform is the most important for businessmen and investors, especially if they are uncertain about the timing of the overall benefits of tax reform. In countries with an active stock market, whether an established one, as in many developed countries, or an emerging one, as in Thailand, the immediate effect of the tax reform may be a revaluation of investors' wealth in the stock market. If the stock market is efficient, the cross-sectional effects of tax reform will be incorporated into stock prices as soon as news about the tax reform reaches the market.

This paper explores the interaction between public finance and financial economic theory in terms of how stock prices react to tax changes. As stock markets become more important in raising and allocating funds for investment in the economy, fiscal planners will grow increasingly concerned about the effects of tax reforms on the stock market and how these may lead to an indirect redistribution of wealth. Since the value added tax and the growing stock market are two crucial public policy issues in many developing countries, the findings in this paper will also be of interest to public policy makers.

With respect to this episode of tax reform in Thailand, this paper raises the following question: "Do stock prices respond to news about tax reform in a way that conforms to the predicted cross-sectional effects?"

The event study method will be used to address the above question. This method has been applied to a variety of economic events. For example, Cutler (1988) tested the effects of changes to corporate income tax brought about by the Tax Reform Act of 1986 on firms in the New York Stock Exchange. He could not reject the hypothesis of zero abnormal returns for most industries and found that there were only weak correlations between predicted effects and actual effects. Thompson (1991) investigated the anticipated sectoral adjustment in response to the Canada-United States Free Trade Agreement. She found that only a few of the abnormal returns on industry portfolios were statistically significant, but that all of them changed in the anticipated directions.

The data used in this paper are stock prices from the Securities Exchange of Thailand (SET). The SET was established in 1975, and at the end of 1991 its market capitalization was about 30 percent of the GDP, with 227 companies listed. These companies represent the diversified economic base of the Thai economy.

The main finding is that tax reform does not generate significant abnormal returns in the stock market, and the reaction of stock prices is not obviously consistent with the cross-sectional effects of tax reform. Within the framework of the event study method, this result implies that this type of tax reform does not have strong cross-sectional effects. The experiment in this paper has a joint hypothesis regarding

tax reform effects and stock market efficiency. It involves a version of the Efficient Market Hypothesis, which states that stock prices react immediately to public information announcements and fully reflect all publicly available information. The issue of stock market efficiency is still controversial, despite a large body of literature that examines this question based on stock markets in the developed world. Less is known about the efficiency of emerging stock markets, including the SET, since few studies address this issue. If convincing evidence of stock market inefficiency on the SET can be shown elsewhere, then this paper's finding that stock prices do not react to tax reform implies that the traditional model of interaction between tax changes and the stock market needs to be revised in view of new stock price-formation mechanisms of an inefficient stock market. Both interpretations of this result have important implications, and each invites more research to be done.

The organization of this paper is as follows: Section II outlines the tax reform process and news, Section III looks at old and new tax regimes, Section IV examines the cross-sectional effects of reform, Section V outlines event study methodology, Section VI gives a description of the data and test procedures, Section VII shows the test results, and Section VIII is the conclusion.

II. The Tax Reform Process and News Events

The idea of replacing the Manufacturing Sales Tax (MST) with a Value Added Tax (VAT) was conceived of in the Thai Ministry of Finance around 1988. Although the detailed package of changes had not yet been worked out, the idea clearly drew such

an unfavourable reaction from business circles that the attempt to push for the reform gradually disappeared from public attention. In recounting the history of the VAT in Thailand, it is often noted that the VAT was not implemented earlier because the coalition government in Thailand, composed of various political parties and commanding only a small margin of seats in the Parliament, could not afford to upset the business community.³

In February 1991, the "democratic" government was deposed in a coup d'etat. The National Peace-Keeping Council later appointed an interim government; the Finance Minister of this new government was well known as the mastermind behind the earlier VAT initiative. The new government undertook a series of new economic measures that had, for some time, been considered difficult to implement, such as ending the protection of the domestic automobile industry. The unveiling of an official sales tax reform package occurred in July.

Four events served to mark important stages in this tax reform. On July 17th, 1991, the Economic Affairs Screening Committee approved the VAT draft bill and sent it to the Cabinet. On July 23rd, two significant news items occurred: the Cabinet approved the draft bill and forwarded it to the National Legislative Assembly (NLA), and the Prime Minister gave an interview on television announcing the implementation date of the VAT as January 1st, 1992.⁴ On August 9th, the VAT bill passed the first reading in the NLA and went to the Public/Private Scrutinising Committee. On

³ For example, see *The Thai Stock Market Compendium 1992*: 108.

⁴ *The Bangkok Post* 24 July 1991.

October 4th, the bill returned to the NLA and passed the second and third (final) readings on the same day. News about each of these events appeared in the leading daily newspapers one day after their occurrence.

These news items seem to represent important events. However, a stock market reaction is likely to occur in response to the events, if any, that convey important news about the tax package to investors. Thus, other conditions surrounding the release of each news item must be taken into consideration.

There are reasons to doubt the importance of three of these potentially newsworthy dates. As mentioned earlier, this appointed government had relatively strong leverage in implementing difficult economic policies. Both domestic and international media at the time portrayed this government as formed of a group of highly capable technocrats who knew what was good for the economy and were not afraid of acting on that knowledge. It is also clear that tax reform and the introduction of the VAT were at the top of the economic agenda that this government announced when it took power.⁵ Thus, the possibility that the Cabinet might reject the draft bill was minimal, so the news of Cabinet approval did not surprise the public.

The public might also expect the two events that occurred in the NLA, for two reasons. First, the new election date was already scheduled. The opposition parties had no hope of gaining politically by trying to oppose the bill. Under normal circumstances, many aspects of the bill could have been criticized in order to create political instability for the government. As it turned out, however, most of the NLA

⁵ See Thai Technocrats Push Through Financial Reforms, *Far Eastern Economic Review* 18 April 1991: 69.

members sought clarifications rather than opposing the bill in the first reading, and the bill later sailed through the second and final readings on the same day. Secondly, many seminars intended for businessmen on preparing for the VAT began to be offered after Cabinet approval of the bill, even before the NLA passed it into law.⁶ Thus, as far as this tax reform was concerned, the NLA may have acted only as a rubber stamp for the government decision. One potential event date, July 17th, 1992, is a stronger candidate than the others in terms of representing the day that the news of tax reform reached the stock market.⁷

Throughout the reform process, the VAT bill was left virtually unchanged. Lobbying by individual industries in Thailand has not reached the same intensity and visibility as in Western countries. Only the effect of the reform on the air transportation industry may have been altered by a change in the VAT proposal during the legislation process. Domestic air transportation was under VAT coverage until the first reading in the NLA; in the second reading it was given exemption status. Unfortunately, only firms engaging in sea transportation were listed in the SET at that time, thus this differential effect could not be tested.

⁶ *Industry Magazine* June 1992: 84.

⁷ All four potential dates will be investigated later by the event-study method.

III. The Old and New Tax Regimes

The pre-reform sales tax in Thailand, the MST, was a single-stage sales tax collected at the manufacturing level.⁸ The tax basis was the gross receipts of importers, manufacturers and operators. Activities subject to sales tax were classified into 14 categories, namely: the sale of goods; rice-milling and saw-milling; the sale of securities; contract work; property rentals; warehousing; the hotel and restaurant industry; transportation; pawn brokerage; brokerage and agency; real estate; banking; insurance; and entertainment.

Each category had its own tax schedule, with the one for sale of goods being the most complex. All goods were distributed into 8 groups to which were applied 13 tax rates ranging from 1% to 50%. Additional complications included numerous Royal Decrees, Ministerial Instructions, Ministerial Notifications and Departmental Instructions which affected tax collection. As a result, some goods were subject to different tax rates depending on who paid the taxes. In general, domestic manufacturers paid lower taxes than importers of the same goods.

The Thai economy has changed in several aspects since the inauguration of the MST. The manufacturing sector has replaced the agricultural sector as the main production base, and the economy has experienced a period of high export-led growth. Criticisms about the MST, with its special rules and exceptions, also increased during this period. The MST has six main drawbacks. First, there is the problem of double taxation. As production grows increasingly specialized, goods that pass through

⁸Sahasakul (1987) provided an extensive description of the pre-reform sales tax system.

multiple production stages are taxed more than once. This cascading or pyramiding effect makes effective tax rates higher than statutory tax rates. Secondly, importers have a tax advantage over domestic producers since they can avoid the aforementioned effect. Thirdly, taxes embedded in domestic tradables reduce the competitiveness of exporters. Tax refunds for exporters provide only partial relief, but they result in the initiation of countermeasures by trading partners since such refunds violate GATT rules. Fourthly, taxes are levied on machinery and, as such, are a disincentive to investment. Fifthly, high effective tax rates may encourage high tax evasion.⁹ Finally, the tax system favours vertical integration over specialization.

The new tax package replaces the MST by a broad-based consumption-type VAT.¹⁰ Taxes are levied on sales/purchases at every stage of production, including manufacturing, wholesale, and retail. However, all input tax that producers pay for their investments and raw materials is refunded in full. Goods and services that are exempted from the VAT include agricultural products, animals (live and meat), eggs and milk, fertilizers, animal feeds, newspapers, magazines, journals, textbooks, labour contracts, rental of real estate, amateur sports tournaments, domestic transportation, and services rendered by hospitals, schools and universities, libraries, museums, zoos, doctors, auditors, lawyers, as well as sales or services to government agencies. The normal VAT rate is 7%. A zero-rate VAT is applied to exports, services performed in Thailand but used overseas, international transportation by air or sea, sales and

⁹A study which directly addressed this question is Thailand Development Research Institute (1987).

¹⁰Price Waterhouse (1991) and Baring Securities Limited (1991) gave a brief summary of the VAT in Thailand.

services to government agencies under foreign aid, sales and services to the UN, embassies and consulates, and sales and services between bonded warehouses. The VAT is impractical for some industries, namely banking, finance and securities, life and non-life insurance, pawn shops and property development. These activities pay at a special sales tax rate of 2.5% to 3.0%. All firms with gross annual revenues over 1.2 million baht¹¹ fall under VAT coverage. Firms with gross annual revenues between 0.6 and 1.2 million baht pay 1.5% tax on their gross revenues. Small firms whose earnings do not exceed 0.6 million baht are exempted from sales tax.

IV. The Cross-Sectional Effects of Tax Reforms

Two independent studies predict the cross-sectional effects of tax reform in Thailand. The study entitled "The Effects of VAT on Prices, Income Distribution, Exports and Export Incentives" is an unpublished document prepared by the Social Research Institute (SRI), Chulalongkorn University, for the Fiscal Policy Office of the Ministry of Finance. Another study, "VAT: Thailand Taxation Review", is a publication of Baring Securities Limited, which aims to disseminate information for professional investors. The summary of Baring Securities' analysis was published in the business section of a leading newspaper on January 1st, 1992, when the new tax regime officially began.

The main benefits of tax reform that are often cited to justify the new tax package are that such reform will result in an increase in overall economic efficiency,

¹¹ The baht is the Thai unit of currency. Approximately 20 baht equalled 1 Canadian dollar at the beginning of 1992.

owing to a reduction of double taxation and of production costs, an increase in the competitiveness of exports, greater incentives for investment and less tax evasion. The SRI study supports the view that tax reform results in an overall benefit. The computable general equilibrium model constructed by the SRI and applied to the Thai economy is used to project the effects of tax reform on the aggregate economy and the disaggregate effects on 17 economic sectors. The results focus on the following variables in each sector: export prices, composite commodity prices, value added prices, net income, private consumption demand, investment, exports, domestic final demand, output, and labour demand. Net incomes are used to represent the predicted cross-sectional effects of tax reform from this study and are reported in Appendix 1. The SRI study also presents a micro-study of representative firms from 7 industries, namely, garments and textiles, electrical instruments, automobiles, food processing, agricultural machinery, jewellery and other export-oriented industries. The result of this micro-study confirms the direction of effects seen in the macro-study.

It should be noted that the SRI model is a static general-equilibrium model. Savings are a fixed proportion of income. Investments are constrained to be equal to savings as a closure rule. Thus, the study does not capture the benefits of tax reform on investment and capital accumulation.¹² Besides, the SRI model is the only macroeconomic model used to study the reform. Surprisingly, no macroeconomic

¹² Progress and problems of the dynamic CGE-tax model are discussed in Pereira and Shoven (1988). Studies done by Hamilton and Whalley (1989) and Hamilton and Kuo (1991) on similar tax reform in Canada use the dynamic model or include in the static model the effects on cost of capital and investment.

studies have been done on the cost of reform, such as inflation and unemployment during the transitional period.¹³

The study by Baring Securities focuses on the effect of reform on firms listed in the SET, classified by industry. The skeleton of the analysis is the industries' production processes, from which changes in tax liabilities and production costs are derived. Expert judgement is used to decide a firms' pricing behaviour and how the tax burden is passed on. Compared to the SRI study, this analysis incorporates more details of the specific industrial environment and firm idiosyncracies, such as the level of competition in business, the tax evasion status of suppliers in industry, and future investment plans, existing sale contracts, and so on. Unlike the general equilibrium analysis, the Baring Securities' study pays relatively little attention to the effects of relative price changes and induced demand shift. The cross-sectional effects of reform predicted by this study are reported in Appendix 2.

This paper takes these two sources of analysis and groups the firms on the SET along industry lines in accordance with whether the firms are predicted to gain or lose from tax reform, as shown in Table 2. In the first three groups (Gainers, Losers, and Neutral), predictions from both sources either agree, or disagreement does not arise since a particular industry is covered by one study and not by the other. The gainers category also includes cases where the SRI predicts positive effects and Baring Securities predicts neutral effects. However, contradictory results arise for two industries. The SRI predicts positive effects for the Jewellery business and negative

¹³ See Capros, Karadeloglov and Mentzas (1990) for a contrast of the two approaches. A study of the short-term cost of sales tax reform in Canada is found in Dungan and Wilson (1989).

effects for the Hotel business, whereas Baring Securities predicts the opposite effects for both industries: .

V. Event Study Methodology

The event study method can be used to investigate the impact of a particular event on stock returns.¹⁴ The impact will show up as abnormal returns if the stock market is informationally efficient. Abnormal returns are defined as the difference between actual returns and the benchmark normal returns that would have been realised had the event not occurred. The most popular return-generating process for the prediction of normal returns is the market model. It can be expressed as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad (1)$$

where R_{it} is the returns to stock i at time t

R_{mt} is the returns to market portfolio at time t

ε_{it} is the stochastic error term of stock i at time t .

The coefficient β_i is the systematic risk of stock i . This is the risk associated with stock i , which cannot be fully diversified. The statistical expression for β_i is $\text{cov}(R_i, R_m) / \text{var}(R_m)$. The error term is assumed to have a mean of zero and constant variance, thus abnormal return is the residual of equation (1). There are alternative

¹⁴ The event-study method was initially designed and used to test the semi-strong form of the Efficient Markets Hypothesis, and later became the basic methodology for value event studies (Salinger, 1992b: 671). Fama(1991) stated that the evidence from event studies is mostly in support of stock market efficiency.

return-generating processes. For example, the market-adjusted return model assumes that α_i is zero and β_i is unity. The mean-adjusted return model sets α_i to a constant mean return and β_i to zero. In the former model, the abnormal return is the difference between individual stock returns and market returns. In the latter, the abnormal return is simply the deviation of returns from their previous average. However, the market model has the advantage of including in the analysis more information concerning the relationship between the returns of a security and the market.

The calculated abnormal returns will be tested against the hypothesis that abnormal returns do not differ significantly from zero. There are proponents of both parametric and non-parametric tests. The important point is that the actual empirical distribution of the test statistic should be the same as that assumed under the null hypothesis, otherwise it will lead to a false inference.

The Brown and Warner (1980) comparative study on event study methodologies for monthly data concludes that as a general rule there is no advantage that would justify the use of a more complicated model of return-generating processes than the market model. Brown and Warner (1985) extend their investigation to the case of daily data, which contains many potential problems for event study such as non-normality, non-synchronous trading and estimation of variance. Non-synchronous trading is a problem for ordinary least square (OLS) estimations of the market model, since β -coefficients will be downward-biased for securities that are traded infrequently and upward-biased for ones that are traded frequently. The problems related to the estimation of variance are autocorrelation, the cross-sectional dependency of returns

and the increase in variance around the day of the event. Cross-sectional dependency can be caused by event clustering, especially if events affect securities on the same day. The increase in variance is usually observed for days around an event. This makes the use of estimated pre-event variance for inferences inappropriate. According to the Brown and Warner simulation, non-normality and non-synchronous trading are not serious problems, and they confirm the robustness of using an OLS-market model and parametric tests for event studies, even with daily data. The adjustment for variance estimation may be necessary for an accurate test if the variance-related problems are strong.

One approach of the event study model is to estimate the market model first, normally using pre-event data.¹⁵ Event-day returns are then predicted, and abnormal returns are calculated as the residual of true returns based on observed data and the predicted returns. Thus this approach is called a two-stage residual analysis. Another approach, the dummy variable approach, rewrites the abnormal returns expression as:

$$R_t = \alpha + \beta R_{mt} + AR_t + \varepsilon_t \quad (2)$$

The market model is estimated with an additional regressor, the dummy variable, which takes the value of 1 on the event date and 0 on all other dates. The data used in the estimation include those for the date of the event. The dummy variable approach is a convenient method for obtaining the forecasting error and the standard

¹⁵ Estimations on the basis of post-event data are appropriate for certain events. See Salinger (1992b).

error of forecast.¹⁶ Thus, the abnormal returns and their standard deviation can be read directly from the estimated coefficient and standard deviation of the dummy variable.¹⁷

VI. Description of Data and Test Procedures

The daily stock prices for all quoted firms between January 1, 1990, and June 30, 1992, are obtained from the SET. The dividend data are recorded in the Fact Book published annually by the SET.

For each firm, daily returns are calculated from the price and dividend data, in accordance with the following formula:

$$R_{it} = (P_{it} + D_{it} - P_{it-1}) / P_{it-1} \quad (3)$$

where R_{it} is the return to stock i at time t

P_{it} is the closing price of stock i at time t

D_{it} is the dividend paid to holder of stock i at time t

P_{it-1} is the closing price of stock i at time $t-1$

¹⁶See Salkever (1976).

¹⁷ Thompson (1985) explains the comparability of the multiple-regression method, which includes event period data, and a two-step residual analysis, which uses only non-event periods in the market model.

Since the reported prices in the data base are already adjusted for stock-splits, these computed returns series are the returns adjusted for dividends and stock-splits. The returns on a market portfolio are computed as an equally weighted average of all individual stock returns. This approximation of market returns is highly correlated with the published SET index, which is a value-weighted index of stock prices unadjusted for dividends. The Pearson correlation coefficient of the two series is 0.98.

The first group of tests is performed at the industrial level. Firms are grouped in accordance with their sectoral classification, and returns on industrial portfolios are formed as an equally weighted average of all firms in the respective industry. Firms qualify for the test if they have been quoted on the SET for at least 250 trading days prior to the first event date. Since no firms qualify in the communications and machinery & equipment industries, 31 industrial portfolios are available for the test. Most of the sectoral classifications conform to those used on the SET,¹⁸ except for the building & furnishing materials and the property development industries. The former is separated into ceramics, cement, and building & furnishing materials, while the latter is separated into contractors-construction and property development, in order to match properly with the predicted effects of tax reform. The predicted effects, which had already been gathered, covered 22 of these 31 portfolios.

The tests will examine the abnormal returns of each industrial portfolio on each predefined event date. Event dates are the news-release dates, or the next trading day if the news appeared on the weekend. Estimation of the model is based on return data

¹⁸*The Fact Book '92*, 203-17.

covering 240 days before the first event date and ending ten trading days prior to the event, together with the event-day returns.¹⁹ The dummy variable approach is used, thus there are four additional dummy variables for each market model equation. Estimation for all industries is done simultaneously using seemingly unrelated least-square estimation. Parametric t-tests and nonparametric rank tests are used to test the null hypothesis that these abnormal returns are zero.

In addition to one-day abnormal returns, the cumulative abnormal returns are calculated over the event window for each event. The event window is comprised of three consecutive days, namely, the day an event occurred, the day the news was released and the day after the news was released (two consecutive trading days if the news-release date falls on a weekend). There is a total of eight estimations in the first group of tests, namely, estimations of one-day abnormal returns and of three-days cumulative abnormal returns for each of the four event dates.

The second group of tests is conducted in order to investigate one-day abnormal returns on each of the event dates at the level of individual firms, in order to confirm the industrial-level results. It may be that the results at the industrial level do not represent the general response of the majority of firms in the portfolio, owing to extraordinary movement for a particular firm. For each event, 187 firm-specific abnormal returns are estimated, with 151 of these firms belonging to industries for which predictions are available on the cross-sectional effects of reform.

¹⁹ If an estimation period is too long, the risk is that it may include the structural break in beta. On the other hand, if the period is too short, the estimated beta may not be reliable. The use of 240 pre-event days, ending ten trading days prior to the event, follows the practice of Brown and Warner (1985).

VII. Test Results

The results are reported and discussed in the following order: 1) One-day abnormal returns tests; 2) Competing predictions; 3) Conflict prediction group; 4) Joint hypothesis tests; 5) Nonparametric tests; 6) Firm-specific abnormal returns tests; 7) Alternative information sets; and 8) The relationship between abnormal returns and the estimated effects of tax reform. Estimations and tests based on a three-day event window are not reported, since the conclusions that can be drawn are similar to those based on one-day abnormal returns.

1. One day abnormal returns tests

The detailed results of estimated abnormal returns and standard errors are reported in Table 3. The first observation is that for most portfolios, on each date, the estimated abnormal returns are small in comparison with their standard errors. The results of tests on these four dates reveal only eight occurrences where a particular portfolio has abnormal returns that differ from zero at or above the 5% level of significance. Secondly, the signs of abnormal returns are mixed; some portfolios do conform to predictions and some do not. On each date, 7 out of 14 portfolios in the Gainers group have the predicted sign. In the Losers group, out of four portfolios one or two have the predicted sign. Thus, for the Gainers and Losers groups, only half the industries reacted as predicted. Moreover, the set of portfolios that conform to predictions changes from date to date.

Table 4 shows the correlation of abnormal returns for each date-pair. If tax news on these dates is important and conveys a similar message of tax reform that

investors will take into account, strong positive correlations are expected. The table reports pairwise correlations and p-values under the null hypothesis that no correlation exists on each date-pair. The pairwise correlations of abnormal returns for all industries and for the Gainers group are weak. The only strong positive correlation is between the first and second dates for the Losers group. On the contrary, for all groups in the table there are relatively high negative correlations. Since the news on each date contains similar information, namely the confirmation of changes to the tax regime, these correlations suggest that tax news does not have a major influence on abnormal returns of industrial portfolios across all dates.

2. Competing predictions

There may be a bias in pooling predictions from two sources to form the Gainers group, since only the first five industries are predicted by both sources to be gainers. For the remaining industries in the group, the SRI predicts positive responses while Baring Securities predicts neutral responses. The results show that most of abnormal returns are not significant, and thus Baring Securities' predictions are arguably closer to the estimated results, while the SRI predictions appear too optimistic in comparison with the reaction of the stock market. However, Baring Securities' predictions do not perform any better than the SRI's in picking the winning and losing industrial portfolios.

3. The conflicting predictions group

In the case of the jewellery and hotel industries, where the two sources of prediction disagree, if the sign of abnormal returns for each industry is consistent across all dates

in the direction predicted by either source, the conflict may be resolved.

Unfortunately, this is not the case. Since there is not enough evidence to indicate that any of these four dates is a better representative of the day the market reacts to tax reform news, the results cannot be interpreted to resolve these conflicting predictions.

4. Joint Hypothesis Tests

Two null hypotheses are tested and reported in Appendix 3. First, the null hypothesis which states that abnormal returns on each date, when considered together, are zero is examined for each industry. The null hypothesis is rejected for only three industries, namely, Professional Services, Warehousing & Silos, and Commerce, all of which are in the No Prediction category. A re-examination of Table 3 demonstrates that the Professional Services and Warehousing & Silos portfolios do not react to news consistently across all dates. However, the Commerce portfolio, which consists of many conglomerates dealing with a wide range of consumer products, appears to be a gainer on all dates. This is puzzling since in this new tax regime the taxes are levied on consumption, and consumers cannot reclaim the VAT. Initially, this should be bad news for the Commerce sector. Further inspection at the level of individual firms will reveal if this reaction can, in fact, be related to tax news.

The second null hypothesis states that abnormal returns for all industries in the same prediction group, when considered jointly, are zero. The tests are performed on each date and the null hypothesis is not rejected in all cases.

5. Nonparametric Tests

The statistical inferences employed so far rely on the assumption that the error component of the estimated market models is normally distributed, with a mean of zero and constant variance. If this assumption is incorrect, it can lead to wrong inferences. Thus, inferences in the event study method are usually strengthened by nonparametric tests, or in some cases by parametric tests based on empirical distribution. Corrado and Zivney's (1992) simulation study demonstrated that the rank test performs better than the parametric t-test and the nonparametric sign test when distributions of abnormal returns are misspecified. The rank test is robust with respect to a variety of misspecifications, including skew, kurtosis and situations where variance increases on the event date. The results of rank tests are reported in Appendix 4.²⁰ The rank test supports the conclusion that few abnormal returns are significant, and the signs of abnormal returns are not clearly related to predictions.

6. Firm-specific abnormal returns tests

The estimated abnormal returns at the level of individual firms are reported in Appendix 5. At the firm level, 18 out of 187 firms have estimated abnormal returns that differ from zero at or above a 5% level of significance on each of the first and the second dates. This number falls to only seven and five firms on the third and fourth dates, respectively.

²⁰ Corrado and Zivney (1992) explain a step-by-step procedure to perform the rank test. The results in this paper are from the Wilcoxon Rank Sum test procedure which is available in the SAS program. Corrado (1989) indicates that these two procedures are equivalent in terms of specification and the power of test.

Based on the pattern of signs, Table 5 demonstrates the percentage of firms in each industry that have the predicted sign of abnormal returns. In some cases the reaction at the industrial level is not representative of what happens at the firm level. For example, it can be seen from rows 1 and 2 that even on the first and second dates, on which these two industrial portfolios do not react as predicted, more than half the individual firms in these industries respond to the news in the predicted direction. Moreover, there are cases where the results of industrial portfolios that conform to the prediction are in fact driven by the reaction of a few firms. For example, on the first event date, only 27% of firms in the insurance portfolio have negative abnormal returns, despite that industry's reaction in accordance with its predicted status of being a loser. However, the number in the last column of the last row shows that on average (across all dates and industries), approximately 48% of firms react as predicted. This number is very close to the results at the industrial level.

The investigation at the level of individual firms does not support the proposition that the extraordinary movements of some firms systematically obscure the responses of industrial portfolios that might actually conform to predictions. As a result, the conclusions drawn from the industrial portfolios test are not mitigated on these grounds.

7. Alternative information sets

Individual investors may know about the effects of tax reform from their dual roles as investors and industrialists, or they may have other sources of information. Their private information sources may give them greater knowledge than that possessed by

economists and financial analysts, therefore the effects of the tax reform will be based on this superior knowledge. In this case, the cross-sectional effects of reform which are manifested through the reaction of stock prices are not necessarily the same as the published predictions. Support for this situation arises if industries and a large number of individual firms in a specific industrial portfolio react consistently across days in which similar news about tax reform is released, even though their reactions may differ from the published predictions of loss or gain.

As discussed before, at the industrial level (Table 3), only the Commerce industry is consistent across all dates and may truly gain from the tax reform. This hypothesis is not supported at the level of individual firms. Table 6 reports the total number of firms in each portfolio in column 2, and the number of firms with consistently positive and negative abnormal returns in column 3 and 4. Column 5 and 6 present the same information as a percentage. The last row shows that the results for the Commerce industry are based on only 20% of the firms in that portfolio, which consistently have positive abnormal returns. Thus it cannot be concluded that the industry as a whole reacts in response to the benefits from the VAT. Not counting the steel industry, which contains only one firm, those industries with a relatively high percentage of consistent gainers are the Food & Beverage industry and the Buildings & Furnishing Materials industry. Overall, it is evident that the majority of industries do not have consistent gainers or losers, and a few have a small portion of firms that behave consistently across all dates. These results are too weak to support the

assumption that there are cross-sectional responses of stock prices to tax reform based on an alternative information set.

8. The relationship between abnormal returns and the estimated effects of tax reform

So far, emphasis has been placed on the binary responses of industry portfolios to tax reform, namely, the status as gainer or loser, as identified by positive or negative abnormal returns. The relatively large standard deviations of estimated abnormal returns indicate that these returns are likely to be statistically insignificant. Another question that can be asked is the following: if there is any relationship whatsoever between estimated abnormal returns of industrial portfolios and the effects of tax reform, which attributes, among the many dimensions of reform effects, are likely to be the main concern of the stock market?

Although the Baring Securities' analysis does not provide any quantitative estimation of reform effects, the SRI CGE-simulation reports separated cross-sectional effects of reform on price, net income of labour and capital, exports, output, employment, consumer demand, investments and imports. Table 7 presents a single regression analysis using estimated abnormal returns on all event dates as a dependent variable and one of the CGE-estimated effects of tax reform as an explanatory variable. In all cases, the relationship between the quantitative effects of tax reform and the abnormal returns is insignificant. The positive sign of coefficients on consumer demand and investments is as expected since increases in these variables are good news for industry, and vice versa. The negative relationship between abnormal

returns and price and between abnormal returns and imports is understandable if increases in these variables signal an increase in the cost of production and a loss of competitiveness of domestic tradables vis-à-vis imports. There is no good explanation for the negative sign on net income, exports and output. The negative sign of the coefficient for employment is an interesting case. It may indicate that general investors focus on short-run adjustments and associate an increase in employment or in the demand for labour in industry, especially at the time of the tight 1991 labour market, with an increase in wages. If investors have different objectives than policymakers, they may extract different information from the same news; good news for one party may signal bad news for the other. The multi-dimensionality of the tax reform effects and the possibility of deviation from the model, which assumes rational investors in an efficient stock market, may account for the lack of a close relationship between stock market reaction and the economic prediction of tax change, as traditional theory posits.

VIII. Conclusion

The test results produce two main findings. First, most of the estimated abnormal returns do not differ statistically from zero. Second, the signs of abnormal returns, both at the industrial portfolio level and the individual stock level, do not follow a pattern consistent with the predicted cross-sectional effects of tax reform. These findings are similar to Cutler's (1988) experience with the 1986 U.S. tax reform.

Event studies are usually subject to a certain degree to doubt about what constitutes an appropriate specification of an event. In the case under consideration in this paper, two alternatives can be considered, which result in two opposite specifications. At one end of the spectrum, one might think that the stock market would have reacted long before the event dates selected in this paper because of the unusual credibility of the interim government. However, this specification is not chosen since it is not clear that the mere announcement of the intention to pursue tax reform provides enough information about the cross-sectional effect of the reform for the stock market to react. A variation of this specification is that the reaction of stock prices may not be synchronous as investors respond to partial news of the reform spread over a long period of time. This alternative will use long-period cumulative abnormal returns, probably starting on the date the interim government was appointed, to detect the effect the event has on stock prices. The problem with this alternative is that the period of study will cover many reforms, all of which have important effects on industry. Moreover, numerous firm-specific events will need to be taken into account. These two factors are difficult to control properly and will weaken the power of the test; therefore, it will not be superior to the identification of the event used in this paper, which is based on the assumption that investors react when the information about the actual tax package is revealed. Under this assumption, the selected event dates are the most promising candidates.

At the opposite end of the spectrum of alternative specifications of the event, one might think that stock prices would react sometime after the selected event dates.

Such a delay will usually occur when there is a possibility that tax changes may be reversed in the near future. There is no evidence that this is the case for this episode of tax reform. When there is no such possibility, the occurrence of a delay would contradict the assumption underlying the event study, namely that investors are rational and stock market is efficient.

When stock prices react in conformance with economic predictions, this validates both the idea of stock market efficiency and the economic theory on which the economic predictions are based. When stock prices do not react as predicted, rejection of tax reform effects or stock market efficiency hypothesis is difficult to distinguish in the results. One interpretation of the results is that this tax reform may not affect firms along industry lines as perceived by economists and financial analysts, for example the impact on the discounted future cash flow of firms is too small, or the impact is distributed in accordance with attributes of individual firms other than that of industry line. Evidence in this direction will shed light on an effect of this tax reform that has so far been overlooked in this tax reform process.

The absence of predicted reactions may be due to market inefficiency, in the sense that stock prices do not react immediately to reflect all available relevant information. Many recent theoretical models of the stock market attempt to formalise how this inefficiency can arise. Some models focus on the importance of information generated by the trading process as opposed to information from outside the market.²¹ Others posit agents who rationally ignore news about fundamentals that conveys

²¹For example, see Romer (1992).

information regarding the true value of stocks.²² These models may support market inefficiency as an explanation of the results in this paper.

This paper's findings are the result of an investigation into an important tax reform in one country's economic history. Similar tax reform has been or will be experienced by many other countries, and many people will, hopefully, find these results interesting, at the very least. However, the more challenging aspect of these results is that they invite more research to be done. Finally, they also cast doubt on the otherwise ready assumption that tax reform has certain effects on the stock market.

²²For example, see Froot et al. (1992).

Table 1: Important Events and News

DATE	NEWS
17 July 1991	Economic Affairs Screening Committee approves VAT draft bill to be sent to Cabinet for approval.
23 July 1991	<ol style="list-style-type: none"> 1. Cabinet approves the draft bill and sends it to the National Legislative Assembly (NLA) for scrutiny. 2. The Prime Minister announces on a television interview that night that "The launching date of the VAT is January 1st, 1992."
9 August 1991	The VAT bill passes the first reading in the NLA and goes to the Public/Private Scrutinising Committee before returning to the NLA.
4 October 1991	The VAT bill sails through the second and the third (final) readings in the NLA.

Source: *The Nation* and the *Bangkok Post*. The news appeared in the daily newspaper one day after the date of the event.

Table 2: Predicted Gainers/Losers along Industry Lines

<u>Gainers</u>	Food & Beverage Textiles, Garments, Footwear Transportation Ceramics Cosmetics Agriculture Automotive Cement Contractors, Construction Electrical Appliances Mining Petrochemicals, Petroleum, Rubber & Plastic Products Pulp & Paper Steel, Machinery Communication
<u>Losers</u>	Banking Finance Insurance Property Development
<u>Neutral</u>	Electronic Components Publishing/Advertising
<u>Contradictory</u>	Jewellery Hotels

Table 3: Estimated Abnormal Returns at the Industrial Level

INDUSTRY	DATE1	DATE2	DATE3	DATE4	STD.ERR.
GAINERS					
1.Food & Beverage	-0.0114	0.0165	-0.0027	0.0107	(0.0143)
2.Textiles,Garments, Footwear	-0.0050	-0.0059	-0.0005	0.0001	(0.0141)
3.Transportation	0.0107	0.0107	-0.0107	0.0104	(0.0268)
4.Ceramics	-0.0022	0.0124	0.0005	0.0060	(0.0164)
5.Cosmetics	0.0033	0.0529	0.0088	-0.0630	(0.0357)
6.Agriculture	0.0033	-0.0060	0.0022	0.0071	(0.0098)
7.Automotive	0.0192	-0.0036	0.0098	-0.0137	(0.0177)
8.Cement	0.0125	-0.0165	0.0063	-0.0059	(0.0135)
9.Contractors,Construction	0.0501	-0.0174	-0.0031	-0.0347	(0.0272)
10.Electric Appliances	-0.0096	0.0129	-0.0056	-0.0038	(0.0151)
11.Mining	-0.0160	-0.0249	0.0126	0.0072	(0.0187)
12.Petrochemicals,Petroleum,Rubber & Plastic Products	0.0100	0.0273	0.0439*	-0.0253	(0.0200)
13.Pulp & Paper	-0.0062	0.0082	-0.0166	0.0210	(0.0165)
14.Steel	-0.0387	-0.0130	-0.0498	-0.0053	(0.0343)
LOSERS					
5.Banking	0.0009	-0.0046	0.0039	0.0106	(0.0125)
16.Finance	0.0157	0.0258	0.0002	-0.0116	(0.0140)
17.Insurance	-0.0058	0.0037	0.0050	0.0006	(0.0131)
18.Property Development	-0.0057	-0.0242	-0.0056	0.0038	(0.0181)
NEUTRAL					
19.Electronic Components	-0.0001	0.0008	-0.0231	0.0084	(0.0207)
20.Publishing/Advertising	-0.0039	-0.0008	0.0049	-0.0054	(0.0164)
CONTRADICTORY					
21.Jewellery	0.0205	-0.0255	0.0072	0.0514*	(0.0259)
22.Hotels	0.0024	-0.0068	0.0049	-0.0024	(0.0135)
NO PREDICTION					
23.Buildings & Furnishing Materials	0.0161	-0.0005	0.0158	0.0095	(0.0138)
24.Household Goods	-0.0083	-0.0083	-0.0133	0.0271	(0.0305)
25.Entertainment & Recreation	-0.0020	-0.0090	0.0125	0.0211	(0.0265)
26.Health Care Services	0.0225	-0.0168	0.0378*	0.0103	(0.0170)
27.Professional Services	-0.0834**	0.0308	0.0315	-0.0950**	(0.0218)
28.Packaging	-0.0062	0.0017	0.0056	-0.0156	(0.0092)
29.Warehousing & Silos	-0.0601**	0.0180	-0.0002	0.0215	(0.0173)
30.Energy	0.0175	-0.0050	0.0209	-0.0211	(0.0273)
31.Commerce	0.0182*	0.0272*	0.0052	0.0094	(0.0094)

Note: * significant at a 5% level in the two-tailed test.

** significant at a 1% level in the two-tailed test.

Table 4: Correlations of Abnormal Returns for Each Date-Pair

	DATE2	DATE3	DATE4
ALL INDUSTRIES			
DATE1	-0.2642 (0.1510)	0.1369 (0.4629)	0.2327 (0.2077)
DATE2		0.1680 (0.3663)	-0.5085 (0.0035)
DATE3			-0.3212 (0.0781)
GAINERS GROUP			
DATE1	-0.0265 (0.9283)	0.4557 (0.1015)	-0.4177 (0.1373)
DATE2		0.2890 (0.3162)	-0.4386 (0.1167)
DATE3			-0.3237 (0.2589)
LOSERS GROUP			
DATE1	0.8219 (0.1781)	0.0339 (0.9661)	-0.7165 (0.2836)
DATE2		0.4697 (0.5301)	-0.7615 (0.2385)
DATE3			0.1364 (0.8636)

Note: Pearson correlation coefficients are reported with P-value in parentheses.

Table 5: Percentage of Firms with the Predicted Sign on Abnormal Returns

	NO. FIRMS	DATE1	DATE2	DATE3	DATE4	AVERAGE
GAINERS						
1. Food & Beverage	8	62.50%	75.00%	75.00%	75.00%	71.88%
2. Textiles, Garments, Footwear	23	56.52%	26.09%	60.87%	65.22%	52.17%
3. Transportation	2	100.00%	50.00%	50.00%	50.00%	62.50%
4. Ceramics	3	33.33%	66.67%	33.33%	66.67%	50.00%
5. Cosmetics	1	100.00%	100.00%	100.00%	0.00%	75.00%
6. Agriculture	17	52.94%	23.53%	58.82%	64.71%	50.00%
7. Automotive	3	100.00%	66.67%	66.67%	33.33%	66.67%
8. Cement	3	66.67%	0.00%	66.67%	0.00%	33.33%
9. Contractors, Construction	1	100.00%	0.00%	0.00%	0.00%	25.00%
10. Electric Appliances	7	14.29%	42.86%	28.57%	71.43%	39.29%
11. Mining	3	0.00%	33.33%	66.67%	66.67%	41.67%
12. Petrochemicals, Petroleum, Rubber & Plastic Products	3	66.67%	100.00%	100.00%	0.00%	66.67%
13. Pulp & Paper	3	33.33%	66.67%	33.33%	100.00%	58.33%
14. Steel	1	0.00%	0.00%	0.00%	0.00%	0.00%
LOSERS						
15. Banking	16	50.00%	56.25%	12.50%	25.00%	35.94%
16. Finance	23	17.39%	39.13%	60.87%	86.96%	51.09%
17. Insurance	11	27.27%	45.45%	27.27%	36.36%	34.09%
18. Property Development	5	60.00%	80.00%	60.00%	40.00%	60.00%
Average (Total)	(133)	52.27%	48.42%	50.03%	43.41%	48.53%

Table 6: Proportion of Firms Showing a Consistent Sign on Abnormal Returns

	NO. FIRM	+	-	+	-
GAINERS					
1. Food & Beverage	8	4	1	50.00%	12.50%
2. Textiles, Garments, Footwear	23	3	3	13.04%	13.04%
3. Transportation	2	0	0	-	-
4. Ceramics	3	0	0	-	-
5. Cosmetics	1	0	0	-	-
6. Agriculture	17	0	1	-	5.88%
7. Automotive	3	1	0	33.33%	-
8. Cement	3	0	0	-	-
9. Contractors, Construction	1	0	0	-	-
10. Electric Appliances	7	0	1	-	14.29%
11. Mining	3	0	1	-	33.33%
12. Petrochemicals, Petroleum, Rubber & Plastic Products	3	0	0	-	-
13. Pulp & Paper	3	0	0	-	-
14. Steel	1	0	1	-	100.00%
LOSERS					
15. Banking	16	1	1	6.25%	6.25%
16. Finance	23	1	0	4.35%	-
17. Insurance	11	2	0	18.18%	-
18. Property Development	5	0	0	-	-
NEUTRAL					
19. Electronic Components	3	0	0	-	-
20. Publishing/Advertising	4	0	0	-	-
CONTRADICTION					
21. Jewellery	2	0	0	-	-
22. Hotels	9	0	1	-	11.11%
NO PREDICTION					
23. Buildings & Furnishing Materials	5	2	0	40.00%	-
24. Household Goods	1	0	0	-	-
25. Entertainment & Recreation	1	0	0	-	-
26. Health Care Services	4	1	0	25.00%	-
27. Professional Services	1	0	0	-	-
28. Packaging	9	1	1	11.11%	11.11%
29. Warehousing & Silos	3	0	0	-	-
30. Energy	2	0	0	-	-
31. Commerce	10	2	0	20.00%	-

Table 7: Regression Test of Estimated Abnormal Returns and Estimated Effects of Tax Reform from the CGE Model

	Constant	OLS-coefficient
Price	0.0669 (0.2023)	-0.0037 (0.0244)
Net Income	0.0788 (0.1919)	-0.0003 (0.0029)
Exports	0.0779 (0.2164)	-0.0002 (0.0166)
Output	0.0798 (0.1911)	-0.0186 (0.0421)
Employment	0.0724 (0.1908)	-0.0089 (0.0118)
Consumer Demand	0.0956 (0.2124)	0.0048 (0.0239)
Investments	0.0209 (0.2530)	0.0036 (0.0107)
Imports	0.0645 (0.2034)	-0.0067 (0.0375)

Note: For each regression, the dependent variable is the percentage estimated abnormal returns, the explanatory variable is the percentage change over the base simulation.

Appendix 1

Table 8: SRI Predicted Change of Net Income as a Result of Tax Reform

Sector	Impact
Crops	Negative
Livestock, Forestry, Fishery	Positive
Petroleum, Coal, Other Minerals	Positive
Food Products, Animal Feed,	Positive
Beverages	Positive
Tobacco Products	Positive
Textiles, Paper	Positive
Chemical Products	Positive
Oil Refinery	Positive
Rubber Products, Plastic Products	Positive
Cement and Nonmetallic Products	Positive
Steel, Metal Products, Machinery,	Positive
Automotives	
Other Industries	Positive
Electricity, Gas, Water Supply	Positive
Construction	Positive
Wholesale and Retail, Restaurant,	Negative
Hotel	
Transportation, Communication	Positive
Public Services	Negative
Electrical Appliances	Positive
Jewellery	Positive
Wood Furniture	Positive

Source: Social Research Institute (1991).

Appendix 2

Table 9: Baring Securities' Predicted Overall Impact of Tax Reforms

Sector	Impact
Agriculture	Neutral
Automotives	Neutral
Banking, Finance and Insurance	Negative
Cement	Neutral
Ceramics	Positive
Contractors	Neutral
Cosmetics	Positive
Electrical Appliances	Neutral
Electronic Components	Neutral
Food & Beverages	Positive
Gemstones and Jewellery	Negative
Hotels	Positive
Mining	Neutral
Petrochemicals	Neutral
Property Developers	Negative
Publishing/Advertising	Neutral
Pulp/Paper	Neutral
Steel	Neutral
Telecommunications	Neutral
Textiles, Garments and Footwear	Positive
Transportation	Positive

Source: Baring Research Limited (1991)

Appendix 3

**Table 10: Joint Hypothesis Test of Abnormal Returns for Each Industry
Across Four Dates**

INDUSTRY	F Value	P Value
1.Food & Beverage	0.6499	0.6269
2.Textiles, Garments, Footwear	0.0751	0.9898
3.Transportation	0.1578	0.9595
4.Ceramics	0.1806	0.9485
5.Cosmetics	1.3530	0.2477
6.Agriculture	0.2779	0.8987
7.Automotives	0.5343	0.7106
8.Cement	0.6958	0.5948
9.Contractors, Construction	1.3736	0.2403
10.Electrical Appliances	0.3382	0.8523
11.Mining	0.7806	0.5376
12.Petrochemicals, Petroleum, Rubber & Plastic Products	2.1402	0.0732
13.Pulp & Paper	0.7581	0.5525
14.Steel	0.8842	0.4724
15.Banking	0.2413	0.9150
16.Finance	1.3382	0.2531
17.Insurance	0.1065	0.9803
18.Property Development	0.5051	0.7320
19.Electronic Components	0.3774	0.8249
20.Publishing/Advertising	0.8641	0.9924
21.Jewellery	1.4022	0.2305
22.Hotels	0.1118	0.9784
23.Buildings & Furnishing Materials	0.7788	0.5388
24.Household Goods	0.2834	0.8889
25.Entertainment & Recreation	0.2951	0.8813
26.Health Care Services	2.0003	0.0917
27.Professional Services	9.4940**	0.0001
28.Packaging	0.9442	0.4371
29.Warehousing & Silos	3.6884**	0.0053
30.Energy	0.4091	0.8022
31.Commerce	2.6263*	0.0328

Note: $H_0: ER_{i,t=1} = ER_{i,t=2} = ER_{i,t=3} = ER_{i,t=4} = 0$

* and ** are significant at 5% and 1% levels, respectively.

Table 11: Joint Hypothesis Test of Abnormal Returns Across All Industries in the Same Predicted Group on Each Date

INDUSTRY GROUP	DATE1	DATE2	DATE3	DATE4
Gainers	1.0221 (0.4271)	0.7761 (0.6965)	0.8085 (0.6608)	0.9634 (0.4887)
Losers	0.4350 (0.7835)	1.4084 (0.2283)	0.0827 (0.9877)	0.3015 (0.8771)

Note: $H_0: ER_{1,t} = ER_{2,t} = \dots = ER_{n,t} = 0$

F-statistics are reported with the P-values in parentheses.

Appendix 4

Table 12: Wilcoxon Rank Sums Test of Abnormal Returns at an Industrial Level on Each Date

INDUSTRY	DATE1	DATE2	DATE3	DATE4
GAINERS				
1.Food & Beverage	42 (0.2551)	220 (0.1620)	100 (0.7640)	191 (0.3105)
2.Textiles,Garments,Footwear	74 (0.5017)	65 (0.4236)	129 (0.9203)	140 (0.7969)
3.Transportation	175 (0.4488)	175 (0.4488)	79 (0.5483)	175 (0.4488)
4.Ceramics	112 (0.8976)	193 (0.3105)	128 (0.9316)	161 (0.5772)
5.Cosmetics	135 (0.8525)	224 (0.1456)	167 (0.5201)	76 (0.1341)
6.Agriculture	157 (0.6164)	52 (0.3243)	149 (0.6991)	192 (0.3173)
7.Automotive	209 (0.2142)	106 (0.8302)	181 (0.3992)	52 (0.3243)
8.Cement	203 (0.2474)	30 (0.1939)	174 (0.4574)	82 (0.5772)
9.Contractors,Construction	233 (0.1134)	62 (0.3992)	115 (0.9316)	26 (0.1751)
10.Electric Appliances	53 (0.3313)	208 (0.2195)	71 (0.4749)	83 (0.5810)
11.Mining	46 (0.2841)	18 (0.1417)	192 (0.3173)	170 (0.4927)
12.Petrochemicals,Petroleum, Rubber & Plastic Products	170 (0.4927)	218 (0.1707)	249 (0.0953)	24 (0.1663)
13.Pulp & Paper	79 (0.5483)	180 (0.4072)	44 (0.2742)	215 (0.1844)
14.Steel	73 (0.1620)	88 (0.6371)	50 (0.1134)	111 (0.8863)
LOSERS				
15.Banking	150 (0.6889)	80 (0.5578)	175 (0.4488)	213 (0.1939)
16.Finance	216 (0.1797)	233 (0.1134)	123 (0.9886)	43 (0.2653)
17.Insurance	67 (0.4395)	162 (0.5675)	175 (0.4488)	131 (0.8976)
18.Property Development	83 (0.5816)	11 (0.1167)	84 (0.5968)	146 (0.7315)
NEUTRAL				
19.Electronic Components	89 (0.6473)	141 (0.7859)	22 (0.1577)	175 (0.4488)
20.Publishing/Advertising	94 (0.6991)	121 (0.9999)	160 (0.5870)	88 (0.6371)
CONTRADICT				
21.Jewellery	206 (0.2304)	20 (0.1495)	161 (0.5172)	237 (0.1010)
22.Hotels	148 (0.7044)	76 (0.5201)	168 (0.5109)	108 (0.8525)
NO PREDICTION				
23.Buildings & Furnishing Materials	225 (0.1417)	116 (0.9430)	225 (0.1417)	199 (0.2715)
24.Household Goods	95 (0.7101)	95 (0.7101)	73 (0.4977)	201 (0.2592)
25.Entertainment & Recreation	71 (0.4749)	79 (0.5483)	182 (0.3913)	197 (0.2841)
26.Health Care Services	217 (0.1751)	59 (0.2416)	236 (0.1040)	184 (0.3757)
27.Professional Services	6 (0.1010)	234 (0.1102)	234 (0.1102)	2 (0.8850)
28.Packaging	63 (0.6072)	147 (0.7208)	179 (0.6153)	10 (0.1134)
29.Warehouse & Silo	1 (0.0871)	207 (0.2249)	128 (0.9316)	215 (0.1844)
30.Energy	190 (0.3313)	106 (0.8302)	195 (0.2971)	44 (0.2742)
31.Commerce	236 (0.1040)	239 (0.0953)	176 (0.4403)	210 (0.2090)

Note: Rank scores are reported with the approximate significant level of the T-test in parentheses.
Expected mid-rank (under H_0) = 121.5

Appendix 5

Table 13: Estimated Abnormal Returns at the Level of Individual Firms

INDUSTRY/FIRM (PREDICTION)	DATE1	DATE2	DATE3	DATE4	STD.ERR.
1. Food & Beverage (Gainers)					
FET	0.0194	0.0084	-0.0051	0.0186	(0.0286)
HTC	0.0071	0.0144	0.0029	0.0062	(0.0313)
NSTAR	-0.0820	-0.0011	-0.0828	-0.0102	(0.0485)
PR	0.0042	0.0840*	0.0165	0.0611	(0.0332)
S & P	-0.0137	-0.0130	0.0187	-0.0196	(0.0598)
SSC	0.0123	0.0017	0.0336	0.0044	(0.0278)
TF	0.0005	0.0225	0.0102	0.0192	(0.0300)
TwFP	-0.0391	0.0151	0.0144	0.0063	(0.0332)
2. Textiles, Garments, Footwear (Gainers)					
AFC	0.0119	-0.0152	-0.0103	-0.0505	(0.0316)
BATA	0.0521*	0.0301	-0.0291	-0.0108	(0.0251)
BNC	0.0017	0.0578	0.0038	0.0057	(0.0306)
BRC	0.0028	-0.0087	0.0031	0.0192	(0.0283)
BTNC	-0.0154	-0.0144	0.0034	0.0288	(0.0356)
LTX	-0.0119	-0.0414	-0.0155	-0.0046	(0.0268)
NPK	-0.0957**	-0.0129	0.0169	0.0219	(0.0308)
PAF	-0.0192	-0.0194	0.0187	0.0048	(0.0312)
PG	-0.0625*	-0.0114	0.0156	0.0263	(0.0296)
SUC	0.0200	-0.0218	-0.0151	0.0044	(0.0261)
TICO	0.0138	-0.0101	0.0512	0.0256	(0.0279)
TNI	0.0584*	-0.0061	0.0258	-0.0240	(0.0255)
TPCORP	0.0251	-0.0037	0.0068	-0.0632*	(0.0289)
TR	-0.0505	-0.0347	0.0028	-0.0156	(0.02376)
TRTG	-0.0103	-0.0173	-0.0192	-0.0175	(0.0332)
TTI	-0.0127	-0.0143	-0.0205	-0.0271	(0.0279)
TTL	0.0103	0.0075	0.0097	0.0173	(0.0288)
TITM	0.0003	0.0190	-0.0391	0.0031	(0.0320)
UF	-0.0263	0.0058	-0.0068	0.0205	(0.0324)
UI	0.0598*	-0.0042	0.0047	0.0083	(0.0262)
UPF	0.0012	-0.0089	0.0085	0.0154	(0.0270)
UT	-0.0688**	-0.0117	-0.0298	0.0099	(0.0245)
WACOAL	0.0017	0.0003	0.0027	0.0036	(0.0240)
3. Transportation (Gainers)					
JUTHA	0.0001	0.0365	-0.0398	-0.0109	(0.0337)
RCL	0.0212	-0.0151	0.0184	0.0317	(0.0331)
4. Ceramics (Gainers)					
TGCI	0.0174	0.0041	0.0338	-0.0102	(0.0244)
UMI	-0.0190	0.0879**	-0.0262	0.0165	(0.0309)
RCI	-0.0049	-0.0549*	-0.0062	0.0117	(0.0270)
5. Cosmetics (Gainers)					
S & J	0.0033	0.0529	0.0088	-0.0630	(0.0356)
6. Agriculture (Gainers)					
APQ	-0.0133	-0.0125	0.0999*	-0.0376	(0.0399)
BAP	-0.0102	-0.0068	0.0057	0.0090	(0.0310)
BKP	0.0038	-0.0008	-0.0112	0.0160	(0.0298)
CPF	0.0015	-0.0066	0.0133	0.0166	(0.0296)
CPNE	0.0160	-0.0077	0.0013	0.0117	(0.0327)
KT	-0.0140	-0.0490*	0.0702**	0.0126	(0.0244)
LEE	0.0809	0.0810	-0.0363	-0.0293	(0.0447)
PPC	0.0705*	-0.0342	0.0124	0.0359	(0.0299)
SAICO	0.0033	-0.0184	0.0191	0.0340	(0.0268)
SC	0.0296	-0.0102	-0.0407	0.0084	(0.0313)
SFP	0.0128	0.0386	0.0014	-0.0064	(0.0254)
SSF	-0.0396	-0.0394	0.0205	0.0671*	(0.0292)
TC	-0.0000	-0.0341	-0.0584	-0.0147	(0.0600)
TIPCO	0.0122	0.0025	-0.0173	0.0218	(0.0278)
TWC	-0.0296	-0.0078	0.0012	-0.0189	(0.0306)
UCT	-0.0072	-0.0297	-0.0176	0.0087	(0.0418)
UFM	-0.0611*	0.0324	-0.0256	-0.0148	(0.0300)

7. Automotives (Gainers)					
GYT	0.0079	0.0001	0.0174	-0.0282	(0.0364)
SMC	0.0480	-0.0132	-0.0019	-0.0141	(0.0302)
STC	0.0018	0.0022	0.0140	0.0012	(0.0165)
8. Cement (Gainers)					
SCC	0.0111	-0.0040	-0.0020	-0.0076	(0.0201)
SCCC	-0.0105	-0.0111	0.0050	-0.0068	(0.0221)
JCC	0.0369	-0.0345	0.0160	-0.0033	(0.0271)
9. Contractors, Construction (Gainers)					
STAR	0.0501	-0.0174	-0.0031	-0.0347	(0.0271)
10. Electrical Appliances (Gainers)					
CTW	0.0931**	-0.0433	-0.0029	0.0277	(0.0278)
DTM	-0.0275	-0.0141	-0.0035	-0.0259	(0.0705)
IFEC	-0.0423	0.0460	-0.0065	-0.0553	(0.0379)
SINGER	-0.0149	-0.0033	0.0024	0.0166	(0.0298)
SS	-0.0411	0.0343	-0.0597	0.0040	(0.0402)
SUE	-0.0312	-0.0096	-0.0001	0.0001	(0.0326)
TTT	-0.0035	0.0805**	0.0310	0.0061	(0.0289)
11. Mining (Gainers)					
ATL	-0.0407	-0.0421	0.0244	0.0073	(0.0252)
PDI	-0.0031	-0.0327	-0.0023	-0.0033	(0.0225)
THL	-0.0043	0.0002	0.0156	0.0176	(0.0281)
12. Petrochemicals, Petroleum, Rubber & Plastic Products (Gainers)					
TPC	-0.0481	0.0271	0.0088	-0.0172	(0.0330)
UO	0.0449	0.0456	0.1111**	-0.0464	(0.0406)
UP	0.0333	0.0092	0.0119	-0.0124	(0.0271)
13. Pulp & Paper (Gainers)					
PPPC	-0.0040	-0.0278	0.0019	0.0275	(0.0245)
SPP	0.0231	0.0422	-0.0507	0.0135	(0.0266)
TUPCO	-0.0376	0.0103	-0.0012	0.0219	(0.0267)
14. Steel (Gainers)					
TWP	-0.0387	-0.0130	-0.0498	-0.0053	(0.0342)
15. Banking (Losers)					
BAY	-0.0329	0.0047	-0.0056	0.0155	(0.0223)
BBC	0.0221	-0.0204	-0.0501	-0.0059	(0.0275)
BBL	-0.0056	0.0015	0.0030	0.0041	(0.0223)
BMB	-0.0087	-0.0107	0.0100	0.0281	(0.0282)
BOA	0.0032	-0.0109	0.0143	0.0149	(0.0255)
FBCB	0.0155	0.0071	0.0038	0.0186	(0.0270)
IFCT	-0.0194	0.0095	0.0156	0.0214	(0.0256)
KTB	0.0030	-0.0047	0.0060	0.0127	(0.0258)
LTB	-0.0003	-0.0017	0.0008	0.0018	(0.0210)
NTB	0.0189	-0.0231	0.0042	-0.0162	(0.0319)
SCB	-0.0096	-0.0071	0.0156	0.0251	(0.0244)
SCIB	0.0019	-0.0056	0.0040	0.0178	(0.0251)
TDB	0.0321	-0.0052	0.0070	-0.0148	(0.0287)
TFB	0.0015	0.0077	-0.0113	0.0232	(0.0238)
TMB	-0.0067	0.0044	-0.0046	0.0233	(0.0261)
UB	-0.0000	-0.0000	-0.0000	-0.0000	(0.0120)
16. Finance (Losers)					
ACL	0.0329	0.0372	0.0034	-0.0143	(0.0239)
AITCO	0.0306	0.0156	-0.0160	-0.0158	(0.0257)
AST	0.0112	-0.0150	-0.0057	-0.0204	(0.0247)
BFIT	0.0018	-0.0020	0.0176	-0.0126	(0.0244)
BIC	0.0131	0.0737**	-0.0113	-0.0150	(0.0257)
CMIC	0.0090	0.0567**	-0.0297	-0.0120	(0.0237)
CS	-0.0031	-0.0037	0.0036	-0.0021	(0.0270)
DS	0.0153	0.0446	-0.0038	-0.0276	(0.0244)
FCI	-0.0140	-0.0051	0.0494*	-0.0146	(0.0246)
FINI	-0.0048	-0.0099	0.0035	-0.0081	(0.0437)
GF	0.0087	0.0670*	-0.0246	-0.0286	(0.0234)

ITF	0.0147	-0.0120	0.0135	0.0112	(0.0275)
KK	0.0378	0.0114*	-0.0243	-0.0096	(0.0297)
MCC	0.0521*	0.0139**	-0.0183	-0.0114	(0.0257)
NAVA	0.0570*	0.0176	0.0052	-0.0172	(0.0230)
NFS	0.0114	-0.0121	-0.0071	-0.0136	(0.0239)
PHATRA	0.0321	0.0361	-0.0089	-0.0154	(0.0278)
S-ONE	-0.0175	0.0190*	-0.0108	-0.0202	(0.0340)
SGF	0.0034	0.0109*	0.0930**	0.0041	(0.0290)
SICCO	0.0017	0.0212	0.0193	-0.0168	(0.0301)
TISCO	0.0158	-0.0065	-0.0045	0.0095	(0.0272)
TMF	0.0256	-0.0055	-0.0287	-0.0053	(0.0361)
UAF	0.0268	0.0032	-0.0086	-0.0171	(0.0244)
17. Insurance (Losers)					
AYUCO	0.0037	0.0061	0.0211	0.0236	(0.0267)
AYUD	0.0123	-0.0065	0.0112	0.0078	(0.0386)
BKI	0.0124	0.0125	-0.0112	-0.0111	(0.0279)
BUI	0.0043	-0.0158	0.0513	0.0112	(0.0353)
PHA	0.0242	0.0645*	-0.0336	0.0319	(0.0264)
SCIA	0.0135	0.0128	0.0022	0.0050	(0.0528)
SIC	-0.0291	-0.0201	0.0139	-0.0207	(0.0289)
SMG	0.0028	0.0035	-0.0379	-0.0327	(0.0539)
TCT	-0.0937**	-0.0084	0.0110	0.0014	(0.0320)
TIC	0.0024	0.0009	0.0036	-0.0260	(0.0210)
TSLIFE	-0.0166	-0.0093	0.0231	0.0163	(0.0270)
18. Property Development (Losers)					
AMARIN	-0.0179	0.0097	-0.0043	-0.0136	(0.0310)
PORTUN	-0.0457	-0.0326	-0.0236	0.0097	(0.0279)
LH	0.0290	-0.0563	-0.0176	-0.0133	(0.0556)
MK	-0.0151	-0.0266	0.0001	0.0324	(0.0327)
RR	0.0213	-0.0150	0.0175	0.0038	(0.0481)
19. Electronic Components (Neutral)					
GSS	-0.0153	0.0087	-0.0141	-0.0090	(0.0297)
KCE	0.0390	-0.0092	-0.0257	-0.0042	(0.0276)
SVI	-0.0421	0.0028	-0.0295	0.0384	(0.0357)
20. Publishing/Advertising (Neutral)					
MAT1	-0.0122	0.0460	0.0131	0.0233	(0.0306)
MGR	0.0035	-0.0142	-0.0294	-0.0380	(0.0327)
NATION	-0.0087	-0.0267	0.0057	0.0152	(0.0280)
POST	0.0019	-0.0082	0.0300	-0.0222	(0.0245)
21. Jewellery (Contradictory)					
O-LAP	0.0261	-0.0365	-0.0122	0.0005	(0.0385)
PRANDA	0.0150	-0.0146	0.0266	0.1022**	(0.0333)
22. Hotels (Contradictory)					
ASIA	0.0974**	0.0061	0.0498	-0.0167	(0.0314)
CENTEL	-0.0074	-0.0095	0.0304	-0.0083	(0.0269)
DTC	-0.0083	-0.0112	0.0153	0.0043	(0.0301)
IME	-0.0014	-0.0052	-0.0037	0.0150	(0.0316)
OHTL	0.0226	-0.0005	0.0148	-0.0003	(0.0271)
PYC	-0.0791	-0.0280	-0.0585	0.0163	(0.0499)
RGR	0.0016	0.0267	0.0085	-0.0149	(0.0305)
RHC	0.0356	-0.0226	-0.0113	0.0030	(0.0326)
ROH	-0.0397	-0.0168	-0.0015	-0.0198	(0.0301)
23. Buildings & Furnishing Materials (No prediction)					
ASTL	0.0042	0.0008	0.0067	0.0091	(0.0470)
CIT	0.0009	-0.0086	0.0078	0.0144	(0.0283)
TAG	0.0139	0.0049	0.0177	0.0207	(0.0227)
TCMC	-0.0198	0.0164	0.0563*	0.0037	(0.0264)
TGP	0.0812**	-0.0158	-0.0095	-0.0004	(0.0265)
24. Household Goods (No prediction)					
TCPI	-0.0083	-0.0083	-0.0133	0.0271	(0.0305)
25. Entertainment & Recreation (No prediction)					
CSK	-0.0120	-0.0090	0.0125	0.0211	(0.0264)
26. Health Care Services					

(No prediction)					
BH	0.0494	-0.0561*	0.0017	0.0066	(0.0257)
KDH	0.0106	-0.0426	0.0151	0.0111	(0.0285)
SH	0.0168	-0.0133	0.1109**	-0.0015	(0.0325)
SVH	0.0131	0.0448	0.0239	0.0250	(0.0295)
27. Professional Services (No prediction)					
FE	-0.0834**	0.0308	0.0315	-0.0950**	(0.0217)
28. Packaging (No prediction)					
ALUCON	0.0146	0.0050	0.0059	-0.0149	(0.0202)
CMBT	0.0038	-0.0057	0.0084	-0.0134	(0.0361)
CSC	0.0059	0.0258	0.0079	0.0099	(0.0309)
NEP	-0.0512	-0.0010	-0.0013	-0.0079	(0.0462)
SP	0.0025	0.0040	0.0014	-0.0296	(0.0234)
TFI	-0.0099	-0.0210	0.0077	-0.0437	(0.0292)
TGI	-0.0001	-0.0004	0.0001	0.0003	(0.0055)
TMD	-0.0194	0.0143	0.0197	-0.0020	(0.0304)
TTP	-0.0018	-0.0056	0.0010	-0.0390	(0.0307)
29. Warehousing & Silos (No prediction)					
KWC	-0.0347	-0.0020	-0.0020	0.0965**	(0.0250)
SST	-0.0822**	0.0782*	-0.0027	-0.0186	(0.0311)
UST	-0.0633	-0.0222	0.0036	-0.0134	(0.0348)
30. Energy (No prediction)					
BP	0.0098	0.0008	0.0248	-0.0273	(0.0385)
TIG	0.0253	-0.0108	0.0171	-0.0148	(0.0320)
31. Commerce (No prediction)					
BJC	0.0013	0.0015	0.0005	0.0006	(0.0152)
EAC	0.0103	-0.0063	0.0078	0.0228	(0.0202)
ICC	0.0001	-0.0075	0.0056	0.0107	(0.0226)
MINOR	0.0930*	0.0824*	-0.0226	-0.0390	(0.0397)
NC	0.0159	0.0387	-0.0103	0.0497	(0.0325)
OCC	0.0016	-0.0146	0.0135	0.0064	(0.0348)
SPC	-0.0154	0.0748**	0.0115	0.0216	(0.0280)
SPI	0.0017	0.0714**	0.0477	0.0163	(0.0277)
VK	0.0510*	-0.0328	-0.0062	0.0087	(0.0253)
WG	0.0230	0.0139	0.0039	-0.0043	(0.0263)

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II: Trading Rules, Profit and the Stochastic Properties of Stock Returns in Thailand.

Simple Trading Rule, Profit and Stochastic Properties of Stock Returns in Thailand

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Introduction

During the 1970s, most empirical research into the stock market tended to conclude that stock markets were efficient in the sense that future returns could not be predicted from past and present information. Twenty years later, numerous findings have indicated that stock markets are, on the contrary, not efficient. Two questions that are frequently addressed in the recent literature are first; Can stock returns be predicted and what are the predictable proportions of their variability at various forecasting horizons? Widely cited papers addressing this question include Fama and French (1988) and Poterba and Summers (1988).² Second; Are actual stock returns excessively volatile compared to the volatility that might have been generated by the

¹ Reprinted in Rea (1932).

² Some papers in this group address, directly or indirectly, questions closely related to the topic of this paper, such as whether the signs of excess returns are predictable and whether these predictions can be used in the development of a profitable trading strategy (see Pesaran and Timmermann (1993)). Another interesting question on return predictability is whether extraordinary events such as stock market crashes, in which the rapid run up of stock prices is followed by a sudden collapse, can be predicted. For a discussion of this see van Norden and Schaller (1991).

behaviour of rational investors and the fundamental model, such as the discounted present value of the dividend model? The literature on excessive volatility was pioneered by the variance bound test proposed by Shiller (1981) and Leroy and Porter (1981), and later by more refined tests such as those proposed by Campbell and Shiller (1987).

Another question popular in the early efficient market debate, and one which has recently received renewed attention, is; Do stock markets deviate from an efficient model in such a way that significant profits can be made? The literature on trading rules has tried to answer this question by simulating, ex post facto, simple trading rules based on past and present information available at each trading decision and analyzing the simulated profit. Academics are concerned with establishing a formal relationship between the results obtainable through the application of trading rules and the efficient market literature. This relationship is based on Jensen's (1978) definition of the efficient stock market, which states that "a market is efficient with respect to information set θ , if it is impossible to make economic profits by trading on the basis of θ ." The recent evidence that stock markets may not be efficient has inspired many researchers to reinvestigate trading rule profits on stock markets and other markets, such as the exchange rate market. Recent theoretical models of the stock market have also been postulated to explain the profits generated through the application of trading rules. Examples of these are Brown and Jennings (1989), Frankel and Froot (1990), and Froot, Scharfstein and Stein (1992). In contrast to the periodic interest displayed

by economists, professional investors have always been interested in trading rules. However, their main concern is in the profit-making function of these rules.

A recent and unique contribution to the literature on trading rules is by Brock, Lakonishok and LeBaron (1992), who use simple trading rules together with the bootstrap simulation method as a specification test for many popular stock return generating models. At present, progress in computer technology has made computer-intensive methods of statistical analysis, including randomization and the Monte Carlo and bootstrap methods more accessible to researchers at a relatively low cost. More researchers are demonstrating that these methods are powerful and versatile with respect to a variety of finance and economic problems. For examples, see Kim, Nelson and Startz (1992), Goetzmann and Jorion (1992), and Schaller and Jog (1993). Brock, Lakonishok and LeBaron (1992) give an interesting application of the bootstrap method and trading rules in the area of stock market research.

There is a long history of empirical research on the three aforementioned themes; however, one of the shortfalls of the research is that the majority of studies on stock market efficiency have focused on the stock markets in industrial economies. Despite the current interest of investors in emerging stock markets, far fewer formal studies have been done on their performance. The general perception in the investing community seems to be that the emerging stock markets with, among other things, their relatively less stringent regulations and a lack of supervisory experience, are less

efficient than the mature markets.³ This perception seems to imply that stock markets must achieve a certain size or maturity before they can operate efficiently.⁴ Some of the empirical research done so far on small stock markets does not support this view. For example, in their comparative study of the stochastic properties of daily stock prices on the Copenhagen Stock Exchange between 1890 and 1900, Jennergren and Sorensen (1988) conclude that the market was no less efficient than the Scandinavian stock market in recent periods. For more contemporary evidence, Hawawini (1984) surveys 280 studies written between 1972 and 1984, covering 14 Western European stock markets, and concludes that despite their smaller size and less frequent trading, their stock prices behave similarly to those of the New York Stock Exchange, which suggests that they are no less efficient than that advanced stock market. More empirical evidence from various stock markets and a better understanding of their microstructure are needed in order to explain how specific institutional arrangements affect price formation in stock markets. While present stock market theory has not yet offered guidance on the question of efficiency in emerging stock markets vis-à-vis more mature ones, empirical investigation into the performance of emerging stock markets is an immediate and important task that can shed some light on the issue. More generally, research into emerging stock markets would fulfil a useful agenda by

³ Another important concern of investors is that trading in emerging stock markets may be fraught with price manipulation or insider trading. Economic theory, however, suggests that insider trading can increase stock market efficiency since informed traders actively bring relevant information to the markets and prevent long-lasting deviation of stock prices from fundamental values. See Leland (1992) for a theoretical model and Meulbroeck (1992) for empirical support from U.S. experience.

⁴ For example Calderon-Rossell (1988), 106, says "Thus, the relative small size of emerging markets seems to suggest that they would be less exchange-efficient than developed markets and as a consequence they may also be less allocable and informationally efficient."

accumulating empirical knowledge about the characteristics of emerging stock markets through the application of the same critical methods of addressing stock market issues as applied to stock markets in industrial economies. This paper pursues this agenda by focusing on one of the less studied emerging stock markets in the Pacific basin, namely, the Stock Exchange of Thailand (SET).

The questions addressed in this paper are twofold. First, can simple trading rules generate statistically and economically significant profits in the SET? Second, using profits generated through the application of trading rules as the main criterion, what stock return model is likely to generate returns on the SET? This paper starts by applying simple moving average trading rules to the daily stock prices index of the SET. The data used in simulation begin with the inception of the SET in 1975 and continue to the middle of 1992, providing nearly a complete history of the stock market in Thailand. The profits generated by the application of these rules are investigated and their economic significance is discussed. Then the bootstrap method is used to test which stochastic processes—random walk, the autoregressive model, or the Markov-chain model—are capable of generating simulated profits that closely resemble the profits shown on the actual SET index.

There are three main results. First, trading rules reveal some interesting characteristics for the return series on the SET. When applying trading rules, the mean of returns is high during buy signals and low or negative during sell signals, and the means of both buy and sell returns differ from the average return on the SET index. In addition, the standard deviation of returns is lower during buy signals. These

characteristics indicate that investors can get higher returns with lower risk by using strategies based on the application of trading rules than by buying and holding stocks for the same investment period. Second, further examination supports the finding that the profits obtainable through the application of trading rule strategies are not only statistically significant but also economically significant. Profits are large even when transaction costs are higher than normally specified on the SET. Moreover, profits from the use of trading rule strategies can be made even over the short investing horizon of one year. Third, profits cannot be satisfactorily explained by the random walk model or the Markov-chain model in the bootstrap and Monte Carlo simulations, thus these models are rejected as the underlying return-generating process of the SET data. The autoregressive model of order one partially succeeds in explaining some qualitative characteristics of trading rule profits but does not satisfactorily capture the quantitative aspects.

The paper is organized as follows. Section I is a brief review of the literature on trading rules. Section II presents summary statistics of the SET index. Section III explains simple moving average trading rules and reports the results of simulated applications of these trading rules. The economic significance of profits generated through the application of trading rules is discussed in Section IV. The application of the bootstrap simulation method together with trading rules to test various stochastic return-generating models is described and results are reported in Section V. The test of trading rules with returns generated from a simulated Markov process is done by

Monte Carlo simulation in Section VI. Section VII summarises findings and discusses future directions for research.

I. The Literature on Trading Rules

Investor interest in trading rules, a mechanical trading strategy based on past and present information, especially stock prices, dates back to the Dow Theory in the U.S. during the late 1800s. At that time, stock market regulations governing the disclosure of financial information were inadequate for fundamental analysis to be practical, and the only widely available source of information was stock prices. Even today, when much larger sets of information are made available to stock analysts, the use of trading rules to signal buy and sell decisions—usually called technical analysis—remains as popular as ever. Numerous trading rules have been invented, ranging from very simple ones based on simple moving averages of past prices to very complicated ones incorporating information such as high-order moments of price series and trade volume. Technical analysis commonly looks at the plot of past prices and tries to identify patterns that conform to the description of buy and sell signals in accordance with a particular rule. Thus, technical analysts are sometimes referred to as "chartists". These trading rules, which are usually given as a set of descriptive instructions with fancy names, such as head and shoulders, candlesticks, Elliot's waves, and so on, can often be translated into counterpart rules based on the statistical properties of price series.

Formal study of trading rules started with Alexander (1961). He used a filter rule that generated a buy signal when the daily closing price of a stock went up at least $x\%$ from the past local low and a sell signal when its price went down by at least $x\%$ from the past local high. Various filter sizes ($x\%$) were reported to yield greater profits than did a static buy-and-hold strategy. However, the implication of trading rule results to the theory of stock prices was not without controversy. Fama and Blume (1966), for example, found that when transaction costs were taken into account, mechanical trading rules based only on past and present information could not consistently outperform a simple buy-and-hold strategy. Recently, profits obtainable through the use of a variant of the Alexander trading rule were re-examined based on the availability of longer U.S. stock price series. Sweeney (1988, 1990) found that for traders who faced relatively low transaction costs, such as floor traders, the transaction costs would not wipe out all the excess profits from trading rules. For smaller stock markets, Verga (1988) found that Alexander-type rules and 25-day moving average rules applied to the Italian stock market during 1975–1987 failed to generate profits greater than those generated by a buy-and-hold strategy. Crato (1988) found that Alexander-type rules yielded superior profits than did a buy-and-hold strategy in the Lisbon Stock Exchange between January 1986 and November 1987.⁵ Hawawini's

⁵ However, trading rule profits resulting from simulation over a relatively short horizon or over an arbitrarily selected part of the available time series data are usually viewed with scepticism by both professional investors and academics. This viewpoint is reflected in Lo and MacKinlay (1990) for tests of asset pricing in general, and in Freeman (1992) and Brock, Lakonishok and LeBaron (1992) for the application of trading rules.

(1984) survey of other filter rule tests applied to European stock prices reported that mechanical trading rules failed to generate abnormal profits in most cases.

Trading rules have been used as a research tool by many authors who successfully adapted them to address interesting questions in many areas of stock market research. DeBondt and Thaler (1985, 1987) used trading rule simulations to try to find evidence of market overreaction which might explain excess volatility in stock markets. They employed the rule that defined "winner" and "loser" portfolios based on the historical performance of securities and tested whether their performance was reversed in subsequent periods, compared to that of the market. Bulkley and Tonks (1992) also pursued the question of excessive volatility based on the application of a different mechanism, called a long-term trading rule. In contrast to most tests for excessive volatility, which are regression-based and make restrictive assumptions regarding the existence of a rational representative agent who discounts future streams of dividends to approximate the fundamental value of stocks, the trading rule approach assumes only that an agent exploits information on stock prices up to the current trading period in deciding when to hold a broad-based market portfolio and when to switch to risk-free assets. Bulkley and Tonks found evidence that the long-run volatility of the market may be excessive since it could be systematically exploited to generate greater profits than those generated by a buy-and-hold strategy. Brock, Lakonishok and LeBaron (1992) combined trading rules and a statistical simulation method called the bootstrap technique postulated by Efron (1979) to provide a specification test of a stochastic return-generating model. They demonstrated that

trading rules detected some stochastic properties of stock returns, represented by the daily Dow Jones index between 1897 and 1986, that could not be explained satisfactorily by popular models such as the random walk, the AR(1), the GARCH-M, and the Exponential GARCH. Their trading rule results also posed challenging questions to the equilibrium model of asset prices, which associated higher returns with higher risk, since the buy signals generated by trading rules yielded higher returns but a lower return volatility than did the sell signals. In addition, another feature that the equilibrium asset-pricing model might not be able to explain was that the sell signal appeared to be able to predict negative returns.

II. Historical Behaviour and Sample Statistics of Returns

This section provides background to the behaviour of stock returns on the SET from its inception on Wednesday, 30 April 1975, through to Wednesday, 28 October 1992. The variable to be examined is daily returns in local currency on the SET Index which is the market-value-weighted index of all stock prices not including dividends. Daily returns are calculated as log differences of the SET Index. Ten-day returns are the sum of daily returns over ten consecutive trading days.

Table 1A contains summary statistics of daily returns for the full sample period and six subperiods. The first subperiod is the beginning stage of the SET, during which firms and investors did not participate very actively. The second and third subperiods correspond to the second oil crisis and its aftermath. During the fourth period, the Thai economy pursued structural adjustments and followed strict monetary

and fiscal discipline to cope with a large current account deficit and to regain economic stability. In the fifth period, the economy started to enjoy a high rate of growth stimulated by increasing exports and incoming foreign investment. During the sixth subperiod, the stock market was adversely affected by extraordinary events such as the Iraq War and domestic political turmoil.

The period 1987–89 shows the highest mean returns, at an annual rate of approximately 48%. The period 1978–80 has the lowest and the only negative mean returns of all the subperiods. However, the same subperiod also contains the highest one-day return ever registered in the full sample. The lowest one-day return is in the last subperiod.

The volatility of returns has changed over time. It is constant during the 1975–80 period, declines during 1981–86 and increases again in 1987–92. The most recent period, 1990–92, shows the highest volatility in the history of the SET.

The distribution of returns for the full sample is strongly leptokurtic with a kurtosis statistic of 13.17. All subperiod distributions also have excess kurtosis, although the magnitude decreases in the second half of the sample. The returns also appear to be slightly skewed.

Table 1B shows the sample autocorrelations of daily returns. The Bartlett asymptotic standard deviations are shown in the last row. These are used to test the significance of the autocorrelations under the null hypothesis that the return process is white noise with constant variance. The autocorrelations for the full sample are significant at lags 1 to 4 and lag 10. The largest serial correlation values appeared at

the first lag for both the full sample and all subperiods. These first-order autocorrelation coefficients are all positive. During 1981–1989, the autocorrelations at lags 1 to 4 are all significant, especially during 1984–86, when the values of serial correlations are large and do not decline quickly, even at a long lag, as they do in other subperiods. During the most recent subperiod, only the autocorrelation at the first lag is significant. It is also smaller in comparison with those of the other

Table 1A: Summary Statistics of Daily Returns

	Full Sample	75-77	78-80	81-83	84-86	87-89	90-92
N	4319	659	742	740	740	741	697
Mean	0.00051	0.00091	-0.00051	0.00010	0.00058	0.00195	0.00006
Std.Dev.	0.0124	0.0108	0.0108	0.0060	0.0051	0.0146	0.0204
Minimum	-0.0929	-0.0619	-0.0652	-0.0508	-0.0355	-0.0894	-0.0929
Maximum	0.1035	0.0590	0.1035	0.0436	0.0244	0.0713	0.0866
Range	0.1964	0.1209	0.1687	0.0944	0.0599	0.1607	0.1796
Skewness	-0.4018	0.5005	1.3232	-0.5500	0.0938	-1.4369	-0.2842
Kurtosis	13.17	8.87	15.08	16.15	4.85	8.98	4.83

Table 1B: Autocorrelation Coefficients of Daily Returns

Lags	Full Sample	75-77	78-80	81-83	84-86	87-89	90-92
1	0.227**	0.365**	0.273**	0.224**	0.260**	0.264**	0.146**
2	0.035*	0.006	0.054	-0.107**	0.117**	0.154**	-0.028
3	0.043**	-0.043	0.027	0.129**	0.128**	0.108**	0.014
4	0.077**	0.066	0.041	0.126**	0.092*	0.098**	0.064
5	-0.010	0.051	0.011	-0.014	0.122**	-0.048	-0.032
6	-0.012	0.067	-0.037	-0.060	0.053	0.016	-0.051
7	-0.002	0.099*	0.031	-0.070	0.022	0.002	-0.047
8	0.026	0.073	0.027	0.003	0.105**	0.028	-0.002
9	0.027	0.010	0.049	0.185**	0.108**	-0.012	0.014
10	0.030*	-0.015	-0.000	0.136**	0.101**	-0.018	0.055
20	-0.002	0.020	-0.002	0.038	-0.003	-0.064	0.013
30	0.019	0.031	-0.021	-0.012	0.101**	0.018	0.018
40	0.002	0.018	0.041	0.021	0.087**	-0.058	0.009
50	0.019	0.051	0.010	-0.044	-0.027	0.013	0.015
Barlett Std.	0.015	0.039	0.037	0.037	0.037	0.037	0.038

Note: *,** are significant at the 5% and 1% levels, respectively, for the two-tailed test.

**Table 1C: Autocorrelation Coefficients of Daily Returns
on the SET and on the U.S. market.**

Lags	SET 1975-92	Dow Jones¹ 1897-1986	S & P² 1928-90	CRSP³ 1962-88
1	0.227**	0.033**	0.062**	0.1908**
2	0.035*	0.026**	-0.039**	-0.0107
3	0.043**	0.012*	-0.003	0.0029
4	0.077**	0.046**	0.030**	-0.0048
5	-0.010	0.022**	0.021**	0.0282*

Note: ¹ The Dow Jones Index.

² The Standard and Poor's composite index.

³ The value-weighted index from the Center for Research in Securities Prices (CRSP).

Source: ¹ from Brock, Lakonishok and Lebaron (1992).

² and ³ from Lebaron (1992).

subperiods.⁶ The significant positive autocorrelation of daily returns over a short horizon on the U.S stock market is also found and documented. Table 1C compares the autocorrelation coefficients at lags 1 to 5 from the SET to those on the U.S market, which have been reported in the literature. The autocorrelations at the first lag are much larger for the SET than for the U.S market.⁷

⁶ The mean reversion of stock returns in the SET is another topic of research which remains to be studied. The topic will be interesting in light of contradictory results from the U.S stock market. For example, Poterba and Summers (1988) find that mean reversion in stock returns is reflected in a positive correlation of returns over a short horizon and a negative correlation over a long horizon; on the other hand, Kim, Nelson and Startz (1992) find that mean reversion is a pre-WWII phenomenon and that post-WWII stock returns, in contrast, tend towards mean aversion. The relatively short series of aggregate indices in the emerging stock markets may require the incorporation of information from panel data to improve the tests, as in Jog and Schaller (1992).

⁷ There are many plausible sources of this strong serial correlation, such as infrequent trading, asynchronous trading or changing variances. Lo and Mackinlay (1988) find stronger first-order autocorrelation for the U.S. market when an equal-weighted index is used instead of a value-weighted

Table 2A shows summary statistics of ten-day nonoverlapping returns. In comparison with daily returns, the measure of kurtosis is smaller but excess kurtosis remains for the full sample. Returns also remain slightly skewed. The patterns for the mean and standard deviation are similar to those of daily returns, with the highest volatility in the recent period and the highest mean return during 1987–89.

The ten-day returns are less serially correlated than daily returns. In Table 2B, the first-order autocorrelations of ten-day returns are relatively large and positive for both the full sample and all subperiods except the most recent. They are significant for both the full sample and all subperiods except the 1978–80 and 1990–92 subperiods. There is a tendency for autocorrelation to decline at higher lags, although there are some significant autocorrelations at a higher order for the full sample.

Table 2A: Summary Statistics of Ten-Day Nonoverlapping Returns

	Full Sample	75–77	78–80	81–83	84–86	87–89	90–92
N	431	65	75	74	74	74	69
Mean	0.00504	0.00855	-0.00443	0.00088	0.00594	0.01927	0.00030
Std.Dev.	0.0480	0.0450	0.0463	0.0238	0.0235	0.0577	0.0718
Minimum	-0.2580	-0.1115	-0.1463	-0.0405	-0.0424	-0.2580	-0.2154
Maximum	0.1459	0.1459	0.1270	0.1304	0.0803	0.1253	0.1454
Range	0.4039	0.2574	0.2733	0.1709	0.1227	0.3833	0.3607
Skewness	-0.6151	1.2361	-0.2347	2.2986	0.9932	-1.4988	-0.7765
Kurtosis	4.57	3.22	1.02	11.24	1.44	6.22	1.13

index, thus the source of serial correlation may come from small stocks, which are traded less frequently than large stocks. Further research is needed to verify the importance of each source in the SET.

Table 2B: Autocorrelation Coefficients of Ten-Day Nonoverlapping Returns

Lags	Full Sample	75-77	78-80	81-83	84-86	87-89	90-92
1	0.181**	0.294*	0.137	0.276*	0.364**	0.425**	-0.101
2	0.081	-0.052	-0.063	-0.088	0.198	0.051	0.163
3	0.068	-0.056	0.065	0.055	0.317**	-0.214	0.249*
4	-0.008	0.020	0.167	0.225	0.423**	-0.220	-0.102
5	0.044	0.252*	-0.060	-0.019	0.086	-0.099	0.037
6	0.017	0.262*	-0.072	-0.130	0.127	0.118	-0.205
7	0.094*	0.107	0.110	-0.037	0.276*	0.070	-0.025
8	-0.031	0.166	-0.056	0.203	0.201	-0.123	-0.174
9	-0.050	0.102	0.002	0.041	-0.024	-0.120	-0.179
10	-0.048	0.022	0.027	-0.109	-0.060	-0.082	-0.175
20	0.141**	0.008	0.141	0.075	-0.052	0.024	0.238
30	-0.129**	-0.031	-0.164	-0.091	-0.016	-0.129	-0.234
40	0.045	-0.164	-0.016	0.025	0.031	-0.015	0.079
50	-0.072	0.002	0.015	-0.012	0.056	-0.065	-0.027
Barlett Std.	0.048	0.124	0.116	0.116	0.116	0.116	0.120

Note: *,** are significant at the 5% and 1% levels, respectively, for the two-tailed test when tested with Yule-Walker estimated standard errors.

III. Trading Rules and the SET

While there is no known record of popular technical trading rules in Thailand, the rules used in this paper are similar to those used in Brock et al. (1992). These rules fall under the broad categories of moving average-oscillator and trading range break-out. The underlying logic of these rules is that stock prices have persistent increasing and decreasing trends. If investors can detect the trend in stock prices, they can make more profits than they would using a buy-and-hold strategy by buying at the beginning of the up trend and selling at the beginning of the down trend.

The moving average rules are constructed based on one long-period moving average and one short-period moving average for the past and present price index. If

the short-period moving average is above (below) the long-period moving average, this predicts an up (down) trend in prices, and consequently generates a buy (sell) signal.

$$\text{Let } ma(s)_t = \left(\frac{1}{s}\right) * \sum_{i=0}^{s-1} P_{(t-i)}$$

Then the rule MA(s,S), where $s < S$, is

$$\begin{aligned} \text{signal} &= \text{buy} && \text{if } ma(s)_t > ma(S)_t \\ &= \text{sell} && \text{if } ma(s)_t < ma(S)_t \end{aligned}$$

The moving average pairs used in this paper are (1,50), (1,150), (5,150), (1,200) and (2,200), where the first and second numbers in the parentheses denote the length of short and long moving averages, respectively, of the daily price index. In addition to short-period and long-period moving averages, the band around the moving average can be incorporated in such a way that signals are generated only when the difference between the two moving averages is no less than a prespecified magnitude. This will prevent signals from being generated when two moving averages are only marginally different. This paper will simulate trading rules using moving averages with no band as well as moving averages with a one percent band.

Two ways of using the moving average as a trading rule are studied, namely, the variable-length moving average (VMA) and the fixed-length moving average (FMA). Under the VMA, investors follow all buy and sell signals; under the FMA, investors accumulate returns for a fixed ten-day period after the signal, then liquidate

and wait for next signal. Other signals generated during the ten-day return-accumulating period are ignored.

Another trading rule is called trading range break-out (TRB). The logic of this rule is that investors may form a belief about a reasonable range within which an approximation of the true stock value should fall. This belief will change as time passes. Thus, over a period of time the upper and lower limits of this range form a trading range. The upper and lower limits are widely described in the popular financial press as a resistant and a support level, since there will be more people willing to sell when the price approaches the upper trading range, thereby preventing it from increasing further. The opposite occurs when the price drops to the lower trading range. If the price breaks out of its usual trading range, this new development may lead the market to re-evaluate the range of the true stock value. This break-out may be followed by a trend in prices. For example, the break-out can be led by informed traders and followed by uninformed traders, which creates a trend for prices to move in the direction of the break-out. The TRB rule capitalizes on this observation by using local maximum and minimum stock prices as the resistant and support levels, generating a buy (sell) signal when the resistant (support) level is broken. Thus, in the simulation of these rules, signals are generated when the current price index cuts the local maximum from below or the local minimum from above. When investors observe a signal, they accumulate returns and ignore any new signals for a ten-day period, then watch for the next signal before initiating a new transaction. The local maximum and minimum levels of prices are calculated each trading day

based on the previous 50, 150 and 200 days. The variation of these rules with a one percent band is also studied.

In this section, the VMA, FMA and TRB trading rules are applied to the SET data. For each rule, the following results are reported: the number of buy and sell signals (N_b , N_s), the mean returns under buy and sell signals (m_b , m_s), the proportion of positive returns generated by buy and sell signals, and the spread between mean returns under buy and sell signals ($m_b - m_s$).

The mean buy and sell returns are calculated as

$$\mu_k = (1/N_k) \sum_{t=0}^{N-1} r_{t+1}^k$$

where k is b for a group of returns under a buy signal and s under a sell signal. T -statistics for testing the hypothesis are provided for mean buy returns, mean sell returns and the buy-sell spread. The tests' null hypotheses state that the mean returns under a buy or sell signal generated by the trading rules are equal to unconditional mean returns on the SET index, and that the buy-sell spread is zero. The t -statistics for mean buy and mean sell returns are calculated as

$$t_k = \frac{\mu_k - \mu}{(\sigma^2/N + \sigma^2/N_k)^{1/2}}$$

where N and μ are the number of observations and the unconditioned mean of the sample. The t -statistics for the buy-sell spread are:

$$t_{b-s} = \frac{\mu_b - \mu_s}{(\sigma^2/N_b + \sigma^2/N_s)^{1/2}}$$

Finally, the average of mean buy and sell returns and of the buy-sell spread across variations of each rule is presented.

III A. The Variable-Length Moving Average (VMA) Rule

From the results in Table 3, it can be seen that there are on average 31% more buy signals than sell signals. The number of signals generated is smaller in the instances where the rules are applied using a band than where no band is used. The average one-day return from the buy signals, shown in the last row of the table, is 0.13%, or about 32% at an annual rate.⁸ This return is very high in comparison with the unconditioned one-day return of 0.051% (or 12.6% at an annual rate) from Table 1A. Moreover, it is higher than any one-day return means during all subperiods except the 1987–1989 period when Thailand experienced high economic growth and a stock market boom. For the first six out of ten individual applications of the rule, the null hypothesis that the mean buy returns are equal to the unconditional mean returns is rejected at a 5% level of significance. All six of these applications use the long-period moving average of either 50 or 150 days. The high mean buy returns are in sharp contrast to the mean sell returns, which are all negative, with an average of -0.04% or the equivalent of -9.9% at an annual rate. As in the case of mean buy

⁸ The mean daily returns are annualized by multiplying by 247, which is the approximate number of trading days a year on the SET.

returns, the first six applications of the rule generated mean sell returns that differ significantly from the unconditional mean at a 5% level of significance.

The proportion of buy returns that are positive averages out to about 58%, in comparison with 44% of returns generated by sell signals. This inequality confirms that the rule produces useful signals. The differences between buy and sell returns are positive and statistically significant for all applications of the rule. The null hypothesis that the buy-sell spread is zero can be rejected at a 1% level of significance in all cases. The spread between buy and sell returns is higher for the instances where the rule's application incorporates a 1% band than for those where no band is used.

The pattern of results resembles the simulation done by Brock et al. (1992) using the Dow Jones Industrial Average index, with two differences. First, although the periods under study are not concurrent⁹, the magnitude of returns under buy and sell signals, as well as the buy-sell spread, are much higher in the SET. For example, the average buy-sell spread across all applications of the rule to the SET is more than twice as large as that generated from the Dow Jones Index. This preliminary result implies that trading rule profits are of potentially strong economic significance, an issue that will be explored in the next section. Second, in this study some of the mean returns from buy and sell signals do not differ significantly from the unconditional mean, while the corresponding cases in Brock et al. do. This may be because the test based on the SET lacks power owing to the availability of data from only a much shorter sample period.

⁹ Brock, Lakonishok and Lebaron (1992) used daily data from the Dow Jones index between 1897 and 1986.

Table 3: Test Results for the Variable-Length Moving (VMA) Rule

Test	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1, 50, 0)	2461	1809	0.0016 (3.5922)	-0.0010 (-4.1135)	0.5823	0.4251	0.0026 (6.7199)
(1, 50, 0.01)	2001	1508	0.0020 (4.3976)	-0.0012 (-4.3355)	0.5927	0.4184	0.0032 (7.0023)
(1, 150, 0)	2381	1789	0.0012 (2.1042)	-0.0003 (-2.4578)	0.5745	0.4477	0.0015 (3.9634)
(1, 150, 0.01)	2203	1589	0.0014 (2.5359)	-0.0004 (-2.6555)	0.5851	0.4424	0.0018 (4.3384)
(5, 150, 0)	2375	1795	0.0012 (2.1053)	-0.0003 (-2.4533)	0.5764	0.4457	0.0015 (3.9421)
(5, 150, 0.01)	2197	1598	0.0014 (2.5006)	-0.0003 (-2.1774)	0.5844	0.4499	0.0016 (3.8810)
(1, 200, 0)	2475	1645	0.0010 (1.4366)	-0.0001 (-1.8211)	0.5701	0.4511	0.0011 (2.8315)
(1, 200, 0.01)	2285	1526	0.0011 (1.6744)	-0.0001 (-1.8979)	0.5733	0.4482	0.0013 (3.0172)
(2, 200, 0)	2476	1644	0.0010 (1.4216)	-0.0001 (-1.7973)	0.5703	0.4507	0.0011 (2.7985)
(2, 200, 0.01)	2278	1525	0.0011 (1.5801)	-0.0001 (-1.7305)	0.5720	0.4505	0.0012 (2.7901)
Average			0.0013	-0.0004			0.0017

Note: Rules are represented as (short moving average, long moving average, band).

N(Buy) and N(Sell) are the number of signals generated.

Buy and Sell are the mean daily returns under the signal; the corresponding t-ratios (in parentheses) test the difference between these returns and the unconditional 1-day mean.

Buy>0 and Sell>0 are the proportion of returns greater than zero.

Buy-Sell is the difference between the mean buy and mean sell returns; the corresponding t-ratios (in parentheses) test the difference between these returns and zero.

III B. The Fixed-Length Moving Average (FMA) Rule

Table 4 contains the results from the application of the FMA rule. The signals this rule generates are drastically reduced in comparison with the VMA rule. There are on average 26 buy signals and 22 sell signals for the 17-year trading period, or approximately 1.5 buy signals per year and 1.3 sell signals per year. The FMA

(5,150,0) reported the fewest signals. Most of the t-ratios in this table are very low, which may be due to the small number of signals reported.

The overall pattern of the results is strikingly different from that generated by the VMA rule. Four applications of the rule have negative mean buy returns, which indicates that the strategy may suggest a long position while the stock index is decreasing after a buy signal. Six applications of the rule have positive mean sell returns, indicating that short selling under this strategy will result in losses. In six out of ten instances, the proportion of positive returns was lower under buy signals than under sell signals, and in four cases the spread between the mean buy and mean sell returns was negative.

When looking at individual applications of the rule, it can be seen that FMA(1,150,0), FMA(5,150,0) and FMA(1,200,0.01) succeed in producing positive mean buy and negative mean sell results and a positive mean buy-sell spread. Other applications are not as useful. FMA(1,50,0), FMA(1,150,0.01), and FMA(2,200,0) have negative mean buy and positive mean sell returns and result in a negative mean buy-sell spread. FMA(1,50,0.01) has negative mean returns for both buy and sell signals. The positive spread comes from the fact that the benefits on a short position outweigh the losses on a long position. In contrast, FMA(5,150,0.01) and FMA(1,200,0) have positive mean returns from both buy and sell signals; the positive spreads are the result of larger returns on a long position. Lastly, FMA(2,200,0.01) has small positive mean buy and a positive mean sell returns, resulting in a negative spread.

Unlike the VMA rule, incorporating a 1% band into the application of FMA rules does not always improve the spread, and in fact, can even lower it. This is seen in the pair of instances that use the 150-day moving average.

Averaged over ten applications, the FMA rule generates mean ten-day returns of 0.28% from buy signals and -0.26% from sell signals, resulting in a spread of 0.54%. The mean buy returns are lower than the unconditional mean of nonoverlapping ten-day returns during the sample period from Table 2A, which is 0.5%.

In contrast to the results presented by Brock et al. (1992), the FMA rule does not perform well on the SET. Investors who want to apply a moving average strategy might be better off to follow all signals, as under the VMA rule, instead of ignoring signals and accumulating returns for a fixed duration, as under the FMA rule.¹⁰

¹⁰ These poor results may be due to the small number of signals produced by the application of this rule. A similar experiment was tried using five-day rather than ten-day periods to accumulate returns, and the results are reported in Table 4A in Appendix 1. However, the number of signals increases only marginally, therefore the results do not affect the above conclusion.

Table 4: Test Results for the Fixed-Length Moving (FMA) Rule

Test	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1, 50, 0)	33	39	-0.0002 (-0.6167)	0.0080 (-1.4544)	0.4242	0.4615	-0.0082 (0.7420)
(1, 50, 0.01)	62	39	-0.0007 (-0.9101)	-0.0074 (-1.8832)	0.5323	0.3333	0.0067 (0.8787)
(1, 150, 0)	24	13	0.0051 (0.0118)	-0.0260 (-1.7773)	0.4167	0.4615	0.0312 (1.6270)
(1, 150, 0.01)	25	24	-0.0053 (-1.0299)	0.0039 (-0.1146)	0.5600	0.5833	-0.0093 (-0.6491)
(5, 150, 0)	17	13	0.0122 (0.7148)	-0.0237 (-2.3924)	0.5882	0.3846	0.0359 (2.2500)
(5, 150, 0.01)	16	20	0.0079 (0.2871)	0.0035 (-0.1938)	0.6250	0.6000	0.0044 (0.3566)
(1, 200, 0)	16	19	0.0064 (0.1255)	0.0057 (0.0690)	0.5625	0.6842	0.0006 (0.0458)
(1, 200, 0.01)	26	20	0.0037 (-0.1380)	-0.0037 (-0.9467)	0.5385	0.5500	0.0075 (0.7062)
(2, 200, 0)	13	19	-0.0047 (-0.7290)	0.0059 (0.0957)	0.4615	0.6842	-0.0106 (-0.9276)
(2, 200, 0.01)	24	17	0.0033 (-0.1743)	0.0078 (-0.2154)	0.5417	0.5294	-0.0044 (-0.3660)
Average			0.0028	-0.0026			0.0054

Note: Rules are represented as (short moving average, long moving average, band).

N(Buy) and N(Sell) are the number of signals generated.

Buy and Sell are the mean returns accumulated over ten-day periods after each signal; the corresponding t-ratios (in parentheses) test the difference between these returns and the unconditional nonoverlapping ten-day mean.

Buy>0 and Sell>0 are the proportion of returns greater than zero.

Buy-Sell is the difference between the mean buy and mean sell returns; the corresponding t-ratios (in parentheses) test the difference between these returns and zero.

III C. The Trading Range Break (TRB) Rule

For the TRB rule, the mean buy returns as shown in Table 5 are all positive and differ significantly from the unconditional mean of nonoverlapping ten-day returns; the average t-ratio at which this null hypothesis is rejected is 3.62. The highest mean buy

returns, of 3.44% over ten days, result from the application of the TRB(1,200,0.01). These returns are higher than those unconditional ten-day returns shown during any subperiod of the SET, which peaked at 1.93% during 1987–1989.

Sell signals generated by the TRB rule do not perform well in predicting negative returns since most mean sell returns are positive. They are also statistically insignificant. Only one instance, TRB(1,50,0), has negative mean sell returns. This is the only instance where the hypothesis that mean sell returns are the same as for unconditional ten-day returns can be rejected at a 5% level of significance.

The proportion of positive returns is larger under buy signals than under sell signals, and the buy-sell spreads are positive in all cases. However, for only the first three cases do the spreads differ from zero at a 5% level of significance. Averaged over six instances, the mean buy returns are 2.98%, in comparison with 0.5% which is the unconditional mean of nonoverlapping ten-day returns (Table 2A). The mean sell returns are slightly positive, at 0.46%, which reduces the total gain to the buy-sell spread of 2.52%. Thus, in terms of strategies that accumulate returns over a fixed ten-day period after each signal, the TRB strategy out-performs the FMA. It should also be noted that even though these rules constitute a dynamic trading strategy in which decisions are made every day, profits are generated with a relatively low frequency of trade. TRB(1,200,0.01), which resulted in the highest mean buy returns, generated only 2.6 buy signals per year and only 11 sell signals during the entire 17-year trading period. TRB(1,50,0), which resulted in the highest buy-sell spread, generated an average of 6.8 buy signals and 4.2 sell signals per year. The usual objection to

technical trading rules, that of the high cost of transactions arising from frequent trade, is unlikely to have much bearing on these results. The issue of transaction cost will be explored further in the next section.

Table 5: Test Results for the Trading Range Break (TRB) Rule

Test	N (Buy)	N (Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1, 50, 0)	115	72	0.0246 (3.6393)	-0.0074 (-2.0745)	0.7130	0.4167	0.0319 (3.7719)
(1, 50, 0.01)	68	40	0.0312 (3.8942)	0.0013 (-0.4579)	0.7353	0.5500	0.0299 (2.3288)
(1, 150, 0)	77	39	0.0275 (3.5110)	0.0014 (-0.4225)	0.7662	0.4103	0.0262 (2.2684)
(1, 150, 0.01)	51	18	0.0314 (3.4546)	0.0167 (0.9829)	0.7451	0.6111	0.0147 (0.7300)
(1, 200, 0)	67	30	0.0297 (3.6216)	0.0052 (0.0205)	0.7612	0.4333	0.0245 (1.6684)
(1, 200, 0.01)	44	11	0.0344 (3.5902)	0.0104 (0.2795)	0.7727	0.5455	0.0240 (1.0668)
Average			0.0298	0.0046			0.0252

Note: Rules are represented as (short moving average, local minimum and maximum, band).

N(Buy) and N(Sell) are the number of signals generated.

Buy and Sell are the mean returns accumulated over ten-day periods after each signal; the corresponding t-ratios (in parentheses) test the difference between these returns and the unconditional nonoverlapping ten-day mean.

Buy>0 and Sell>0 are the proportion of returns greater than zero.

Buy-Sell is the difference between the mean buy and mean sell returns; the corresponding t-ratios (in parentheses) test the difference between these returns and zero.

In summary, the results of the VMA rule demonstrate the useful features of technical trading rules: the VMA generates high mean buy returns, negative mean sell returns and a positive mean buy-sell spread. Taken together with the results set out in recent literature, this is evidence in support of the thesis that this rule works in stock markets as diverse as the fully mature New York Stock Exchange (Brock et al. (1992)) and the emerging Stock Exchange of Thailand.

However, these simulations do not provide clear-cut support for the rules based on fixed-length cumulative returns. The FMA rule sometimes produces disadvantageous features such as negative mean buy returns and positive mean sell returns. For its part, the TRB rule, while producing positive spreads, also tends to produce positive mean sell returns, therefore it lacks the ability that other rules based on a moving average possess, that of predicting negative returns. Based on the very small number of signals generated by the FMA and TRB rules, it is suspected that the available SET data may span too short a period of time for an accurate simulation of rules based on fixed-length cumulative returns.

IV. The Interpretation of Trading Rule Results

Two questions arise in interpreting the results obtained from the application of trading rules. The first has implications for asset pricing theory. Trading rules separate returns into two groups based on buy and sell signals, and simulation results show that mean buy returns are higher than mean sell returns. The question is whether higher returns are associated with higher risk. The Capital Asset Pricing Model, based on the optimal portfolio theory pioneered by Markowitz (1952), predicts that a portfolio with higher returns is associated with a higher level of risk. However, Brock et al. (1992) find that trading rule results do not follow this prediction of asset pricing theory. Using a different technique, van Norden and Schaller (1993) discover a similar contradiction. They find that the stochastic property of U.S. stock prices can be

described as a switching process between two regimes, one with a higher mean and lower variance than the other.

The second question concerns the economic significance of trading rule profits. This is an important question since, according to Jensen's definition, a stock market is efficient with respect to an information set including past and present stock prices only when no dynamic trading strategy based on this information set can yield significantly greater economic profits than those generated by a buy-and-hold strategy. Economic profit is defined as risk-adjusted returns net of all costs of implementing the strategy. These two questions are addressed below.

IV A. Risk

To discuss the implications of trading rule results on asset pricing theory, the standard deviation is taken as the simplest measure of risk. The standard deviation of returns during buy and sell signals for each application of the trading rule and for the full sample are presented in Table 6. Buy and sell standard deviations are calculated as

$$sd_k = \left((1/N_k) \sum_{t=0}^{N_k-1} (r_{t+1}^k - \mu_k)^2 \right)^{1/2} \quad k=b, s$$

From the results given in section III, it can be seen that the VMA and TRB rules are more consistent than the FMA in generating higher mean buy returns than mean sell returns. Therefore, they are chosen as the focus.

Table 6: Comparisons of Standard Deviations of Returns

Test	Buy	Sell
The Variable-Length Moving Average (VMA) Rule		
Full Sample	0.0124	
(1,50,0)	0.0111	0.0137
(1,50,0.01)	0.0118	0.0147
(1,150,0)	0.0118	0.0132
(1,150,0.01)	0.0121	0.0135
(5,150,0)	0.0121	0.0129
(5,150,0.01)	0.0121	0.0136
(1,200,0)	0.0120	0.0133
(1,200,0.01)	0.0121	0.0134
(2,200,0)	0.0119	0.0134
(2,200,0.01)	0.0121	0.0134
The Trading Range Break (TRB) Rule		
Full Sample	0.0480	
(1,50,0)	0.0615	0.0468
(1,50,0.01)	0.0670	0.0609
(1,150,0)	0.0696	0.0523
(1,150,0.01)	0.0756	0.0730
(1,200,0)	0.0723	0.0519
(1,200,0.01)	0.0791	0.0631

For the individual applications of the VMA rule, the standard deviations of returns during buy signals are consistently lower than those during sell signals; furthermore, the results in section III show that the VMA rule yields higher mean buy returns than mean sell returns. The standard deviations of returns during buy signals are also consistently lower than those for the full sample despite the fact that the mean buy returns are higher than the full sample mean. For mean sell returns, under the VMA rule the standard deviations are higher, while the means are lower, than those

generated by the full sample. This contradiction to asset pricing theory does not hold for the TRB rule. For all instances of the TRB rule, higher mean buy than mean sell returns are associated with higher standard deviations during buy than sell signals. In comparison with the full sample, most of the returns from the TRB rule conform to the asset pricing theory. The only exceptions are TRB(1,50,0.01) and TRB(1,150,0), where the mean sell returns are lower but more volatile than those of the full sample. Thus, to a certain extent, TRB returns can be explained as the result of a risky dynamic trading strategy. VMA rules, however, consistently defy the asset pricing theory, which predicts a positive relationship between risk and return. Next, the economic significance of profits generated by VMA rules is examined.

IV B. The Economic Significance of Profits

In order to judge the economic significance of profits generated through the application of trading rules, as compared to the use of the buy-and-hold strategy, it is necessary at the very least to examine dividends and the cost of trading. Some studies, such as Fama and Blume (1966), find that when these two factors are considered, the profits generated by the application of trading rule are not significant. Trading rules that require frequent transactions, such as the VMA, are usually subject to this criticism. In addition, much of the recent literature in finance notes that, owing to a variety of reasons, investors may have relatively short investment horizons. Individual investors may have liquidity constraints or consumption plans such that they will need to liquidate their investment in the near future, or fund managers may be subject to

periodic reviews of performance. The use of trading rules that require a relatively long time period to generate profits, especially after a period of sustained poor performance, is not likely to be tolerated by these investors. Therefore, it cannot be claimed that these investors have missed a genuine profit opportunity.

This paper looks at three strategies: Buy-and-Hold (BH), Long/Short (LS) and a timing strategy based on the VMA rule (VT). It is assumed that each strategy is implemented and evaluated yearly, which is a reasonably short investment horizon.

Using the BH strategy, investors buy the portfolio, which yields the same returns as the SET Index, at the beginning of the year, hold it until year-end and then liquidate. They collect all dividends paid during the year without re-investing them. Brokerage commissions are paid at the beginning and at the end of the year when the transactions occur. (The brokerage commission on the SET is 0.5% of buy or sell transactions.¹¹)

Other explicit costs not included in this study are those for computer and data. The cost of data is negligible, since it can be collected from public sources or obtained in machine-readable format from the SET for a small charge. Considered over the long horizon of implementation, these costs, which are constant and do not vary with the frequency of transactions, form only a small portion of the total transaction cost. As such, they play only a minor part in the standard objection to the use of trading

¹¹ As of 1987, Thailand had the second-lowest explicit transaction costs (e.g. brokerage fees, stamp taxes, registration fees) among Pacific Basin capital markets, next to Taiwan. See Rhee et al. (1990) Table 9, p.93.

rules, which, as mentioned earlier, generally focuses on the frequency of trade as the source of high transaction costs.

This study also excludes implicit transaction costs, such as the cost of processing information (person-hours of capable human resources). Since the rules are easy to monitor and operate once they are programmed, this implicit cost is also likely to be small. Another implicit cost is that of executing or matching orders.

Transactions at the closing price may not be available to investors, or they may have to bear the transaction cost from the bid-ask spread. Amihud and Mendelson (1987) comment that trading rule simulations may overestimate profits if the transaction prices reported on the stock market are the intermediate prices between bid and ask prices. To be accurate, buy transactions should be simulated using the quoted ask price and sell transactions using the quoted bid price. Unfortunately, neither trade-by-trade data nor an approximated bid-ask spread is available on the SET. Sweeney (1988) argues that in the presence of a trend, when the trigger price occurs before the closing price, using closing prices in simulation can understate the profits generated by trading rules profit since the actual transactions will occur between the trigger and closing prices.¹² However, academic papers continue to use closing stock prices in effecting simulations, therefore this paper follows suit in order to maintain comparability.

Another, more direct question is whether investors can invest in a market portfolio in Thailand. At present, there is no product on the market that replicates the

¹² See especially footnote 10, p. 234.

performance of the SET Index. However, according to Divecha, Dreach and Stefek (1992), with a combination of approximately 90 stocks it is possible to build a portfolio that can track the SET index within a 1% annual tracking error with a two-thirds probability.

Using the LS strategy, investors act on the signals generated by the VMA rule. During buy signals they take a long position on the stock index and collect dividends; during sell signals they sell short and pay relevant dividends. Commissions are charged every time they buy or sell, and any open position is arbitrary closed at the end of the year, regardless of signal.

The last strategy, VT, uses the VMA rule to time the market. In terms of the present discussion on objections to the use of trading rules, this strategy has the advantage of eliminating the possibility of short selling. Many recent studies, such as Sweeney (1990) and LeBaron (1991) prefer to use trading rules this way. Under the timing strategy, investors hold stocks when the rule produces a buy signal, but instead of short selling they switch to risk-free assets during sell signals. The cost of transferring an investment into and out of risk-free assets is assumed to be zero. The proxy of returns on risk-free asset is the average returns on Government T-bills. However, between October 1989 and the end of sample period, there was no market for Government T-bills in Thailand, so investors are assumed to hold cash as an alternative risk-free asset.¹³ Three applications of the VMA rule are used to generate

¹³ Other possible risk-free assets may be a savings deposit account at the Government Savings Bank, which yields an average annual return of 6.75%, 8.2% and 9% in 1989, 1990 and 1991, respectively. If this alternative is used whenever a T-bill market is not available, the results will improve in favour of the VMA-timing strategy as compared to the buy-and-hold strategy and strengthen the economic

signals, namely, VMA(1,50), VMA(1,150) and VMA(1,200). It should be noted that, owing to the relatively low volatility of risk-free returns, a portfolio based on the timing strategy is generally less volatile than a buy-and-hold portfolio. Sy (1990) emphasizes that the lower volatility of the timing strategy is achieved owing to the greater number of shifts between risk-free assets and equity in its portfolio. Another important point is that investors who use the timing strategy lose the ability to target a particular level of portfolio risk, as defined by beta, which is the correlation between portfolio returns and market returns. In the CAPM context, if investors can borrow and lend freely at a risk-free rate, they can achieve their preferred level of risk using a buy-and-hold strategy by holding equity in exact proportion with the market and then blending this equity portfolio with risk-free assets. These are the trade-offs investors face when using the timing strategy.

Table 7 shows the annual returns from the BH, VT and LS strategies in columns 2–4.¹⁴ Returns from these three strategies are denoted as RBH, RVT and RLS, respectively. The raw returns from the SET index, not including dividends, are denoted as RSET and shown in column 5, and the average dividend-price ratios (D/P) are shown in column 6 for comparison. Columns 7–9 rank the returns from the three strategies.

significance of trading rule profits.

¹⁴ The results of VMA(1,150) and VMA(1,200) are similar to VMA(1,50) as far as the following discussion is concerned, thus detailed results are omitted to save space.

Table 7: Comparing Annual Returns

YEAR	(percent/year)					(rank)		
	RBH	RVT	RLS	RSET	D/P	RBH	RVT	RLS
1977	81.87	78.14	73.40	78.98	2.89	1	2	3
1978	39.85	29.55	15.80	35.16	4.69	1	2	3
1979	-46.20	-6.58	23.97	-54.31	8.11	3	2	1
1980	-9.68	4.08	9.21	-18.02	8.35	3	2	1
1981	-7.20	8.77	14.04	-15.64	8.44	3	2	1
1982	22.72	23.21	16.42	14.76	7.96	2	1	3
1983	14.83	19.82	19.23	8.51	6.32	3	1	2
1984	12.30	8.46	-2.27	5.63	6.67	1	2	3
1985	1.77	11.72	13.66	-5.34	7.11	3	2	1
1986	48.20	46.46	39.58	42.88	5.32	1	2	3
1987	34.44	53.93	72.11	31.86	2.58	3	2	1
1988	32.90	41.78	46.80	30.54	2.35	3	2	1
1989	83.76	68.37	51.37	82.13	1.63	1	2	3
1990	-34.62	6.07	45.97	-36.09	1.46	3	2	1
1991	17.27	20.24	21.87	15.03	2.25	3	2	1
1977-91	19.5	27.6	30.7	14.4	5.1			

Note: RBH, RVT and RLS include dividends and transaction costs.

During 1977-1991, returns generated by the VT and LS strategies are on average 8.1 and 11.2 percentage points higher per year than those generated by the BH strategy. If performance over a short horizon is a concern, the VT strategy outperforms the BH strategy on an annual basis in ten out of fifteen years, with the exceptions being 1977, 1978, 1984, 1986 and 1989. Since only short-horizon investors who started using timing strategy in 1977 would find themselves underperforming the buy-and-hold strategy two years in a row, investors are likely to find the timing strategy useful even over a short horizon. The performance of the LS strategy, however, alternates between highest and lowest ranking among the three strategies; its yields are lower than those of the simple buy-and-hold strategy in six out of fifteen years. Like with the VT strategy, there is only a small chance that short-horizon

investors will find themselves underperforming the BH strategy for two consecutive years.

Table 8 compares the annual profits generated by the application of trading rules as given in Table 7 with profits generated by simulations based on no commission fees and higher fees. The results show that even when the commission fees are raised to 0.75% per one-way transaction, all profits generated by the application of trading rules remain significant. The difference between 0% and 0.75% transaction costs is approximately 4% of profits per year for the VT strategy and 7% per year for the LS strategy.

Table 8: Annual Profits at Different Commission Fees

	RVT			RLS		
	COMMISSION FEES			COMMISSION FEES		
YEAR	0%	0.5%	0.75%	0%	0.5%	0.75%
1977	78.64	78.14	77.88	74.40	73.40	72.90
1978	33.08	29.55	27.78	23.33	15.80	12.03
1979	-3.58	-6.58	-8.08	29.45	23.97	21.23
1980	7.08	4.08	2.58	15.69	9.21	5.98
1981	10.77	8.77	7.76	17.54	14.04	12.29
1982	26.23	23.21	21.69	22.45	16.42	13.41
1983	21.32	19.82	19.07	22.23	19.23	17.73
1984	12.46	8.46	6.46	6.19	-2.27	-6.50
1985	13.75	11.72	10.71	17.19	13.66	11.89
1986	48.46	46.46	45.45	44.08	39.58	37.34
1987	56.94	53.93	52.42	77.61	72.11	69.36
1988	43.29	41.78	41.03	49.80	46.80	45.30
1989	71.38	68.37	66.86	57.87	51.37	48.12
1990	8.57	6.07	4.81	49.97	45.47	43.22
1991	23.28	20.24	18.72	28.43	21.87	18.60
1977-91	30.1	27.6	26.3	35.7	30.7	28.2

The reason that the use of trading rules is very profitable, even at high transaction costs, can be seen from the number of times an investor has to switch between equity and risk-free assets under VT strategy, or between a long position and

a short position under the LS strategy, as reported in Table 9. Even though the dynamic strategy allows trade to occur frequently, the actual pattern of signals requires a relatively small number of transactions. The average switching position is only 9 times per year. For investors whose concern is how often an investment fund is shifted between equity and risk-free assets, Table 9 shows that except for 1977, 1979 and 1989, the proportion of total trading days that the VT strategy places investments in equity as compared to risk-free assets is fairly even. In 1979, the worst year of the SET index, investments are put in risk-free assets on 90% of total trading days, thereby enabling investors to avoid the worst bear market. In addition, in 1990, the second-worst year of the SET, if they follow either moving average strategy investors can still be active on the stock market for about 50% of total trading days and receive good returns.

Table 9: Proportion of Time in the Market and Frequency of Transaction

YEAR	DAYS	BUY	SELL	IN	OUT	NO. SWITCH
1977	246	230	16	93%	7%	1
1978	246	186	60	76%	24%	13
1979	248	26	222	10%	90%	9
1980	248	93	155	38%	63%	11
1981	247	82	165	33%	67%	5
1982	246	141	105	57%	43%	11
1983	247	159	88	64%	36%	5
1984	248	144	104	58%	42%	16
1985	245	113	132	46%	54%	6
1986	247	152	95	62%	38%	7
1987	247	195	52	79%	21%	9
1988	247	153	94	62%	38%	5
1989	247	230	17	93%	7%	13
1990	247	113	134	46%	54%	8
1991	245	118	127	48%	52%	11

The measure of risk used in section IV A is the standard deviation of returns.

If risk is interpreted as only down-side surprise, and the distribution of returns is asymmetric, this measure of risk may be inadequate. The results in this section offer

an opportunity to examine the performance of technical trading rules during the large downturn in the market. Figure 1 plots the annual average daily returns from these three strategies. Returns from the RVT and RLS strategies—both based on the use of moving averages—appear to perform especially well when the market takes a sharp downturn, as it did in 1987 and 1990. The plausibility of performing well in a bear market is very important for dynamic trading strategies. During a bull market the buy-and-hold strategy can perform relatively well since, by definition, it never misses the good state of the market. Thus, RBH returns are higher than RVT and RLS returns in the bull markets of 1977, 1986 and 1989. However, in 1979-81, 1985 and 1990, when the returns from the SET index are negative, returns from the RVT and RLS strategies are substantially higher than those from the RBH.¹⁵ An additional observation that can be made from Figure 1 is that the importance of dividends has declined in recent years as the values of RBH and RSET have become closer. Thus, any disadvantage of using the timing strategy owing to the possibility of missing dividends has declined in importance.

¹⁵ Many formal tests have been proposed to determine whether the timing strategy can predict good and bad market states, more commonly called bull and bear periods (see Henriksson and Merton (1981) and Grinblatt and Titman (1989)). However, this takes us further into a field of finance where there is much debate on how to appropriately evaluate market timing ability.

Figure 1

Figures 2 and 3 chart the BH strategy vis-à-vis the VT and LS strategies based on different moving average lengths. The performance of the VT and LS strategies based on long-length moving averages of 150 and 200 days, relative to the BH strategy, is similar to that based on a 50-day moving average. The sole differences occur in 1988 and 1991 when the two long-length simulations under-perform the BH strategy while the short-length simulation out-performs it.

Figure 2

Figure 3

So far, the discussion about short horizon investments has arbitrarily selected the calendar year as its basis. Thus, the short history of the SET limits the application of trading rules to producing a small number of results. However, there is no reason why short-horizon investments have to begin and end with the calendar year. Annual investments that begin and end on dates separated by only a few days may give drastically different results. To investigate short-horizon investments further, the starting date of annual investments is randomly selected for each of 500 simulations and the rules are implemented. Figure 4 plots the cumulative distribution of annual average daily returns from the BH, VT and LS strategies based on short-horizon investments with 500 random starting dates.

Figure 4

The random starting date simulation seems to confirm that the use of technical trading rules produces less variance than does a buy-and-hold strategy at each level of returns, thus it might be preferred by risk-averse investors.

The discussion of short-horizon performance indicates that RVT is a rule that gives relatively good returns while maintaining an impressive record in outperforming the buy-and-hold strategy on a short-horizon basis during the test period. The RVT is also less risky than an all-equity strategy, since risk-free returns are less volatile than stock markets. The profits generated by the use of the VT strategy are even more impressive considering that this strategy is based on a minimal set of information in comparison with other timing strategies which have been studied on the U.S. market. Fuller and Kling (1990) study a timing strategy that bases the generation of signals to switch between buying and selling on the predicted risk spread. They find that forecasts of stock returns produced by the AR(1) model result in a very poor timing strategy, while forecasts produced by the dividend yield model are useful. However, they acknowledge that their results are ambiguous with respect to the study of market inefficiency since during the 51 years' simulation period their timing strategy put an investment on the stock market continuously for as long as 12 years. From an investor's point of view, this is hardly distinguishable from a buy-and-hold strategy. In addition, at times their timing strategy underperformed the buy-and-hold strategy for prolonged periods. It is likely that investors would have rejected their timing strategy during these periods. In contrast to Fuller and Kling's results, the results in

this paper are free of such ambiguities and provide stronger evidence of economically significant profits.

The next two sections investigate which statistical models commonly used in the literature on finance can explain these trading rule profits on the SET.

V. Bootstraps

The bootstrap method can be used together with trading rules as a specification test for return-generating models. The bootstrap technique was pioneered by Efron (1979).

Under this method pseudo-samples are generated by repeatedly drawing with replacement from the observed realization of random samples, following which the particular statistics under consideration are calculated from these pseudo-samples. When this process is repeated a large number of times, the bootstrap distribution of the test statistics can be used as an approximation of the true distribution, and the original test statistics calculated from the observed sample can be compared to this distribution for statistical inference. The bootstrap technique is flexible and practical. It does not require the probability distribution under the null hypothesis to be completely specified. For example, the theoretical assumption of normally distributed errors is not required since the empirical distribution of errors is used in constructing the bootstrap distribution.

The statistics of interest in this paper are the mean and standard deviation of buy and sell returns and the spread between the buy and sell means generated by the application of technical trading rules. Given the observed stock returns on the SET,

the question is what is their underlying return-generating process. Specification tests of stock return models can be done using an estimation-based bootstrap, as follows. First, the model to be tested is estimated and used as a null model. Then a bootstrap sample of returns is generated from the estimated parameters of the null model and the observed SET data. The precise procedure for this step varies and depends on the null model. The procedure employed for the null model used in this paper will be described in greater detail at a later point. Third, the bootstrap stock returns are transformed into a pseudo stock price index. Following that, the trading rules are applied to this simulated stock price index series, and the statistics under consideration are calculated. These four steps are then repeated 500 times. Finally, once the 500 repetitions have been completed, the statistics generated from the actual SET index are compared to those from the bootstrap simulation. The proportion of test statistics from the simulated series which have a higher value than those from the actual series can be viewed as a simulated p-value. In addition, joint testing of a set of trading rules is done by averaging the simulated p-values across various applications of the rule. This testing would be difficult without the use of the bootstrap technique since otherwise the joint distribution of these rules, which may be dependent, would have to be specified in order to calculate the sampling distribution of the test statistic.

The random walk with drift model assumes that returns are derived from stock prices generated by the following model:

$$p_t = \alpha + p_{t-1} + \varepsilon_t$$

where p_t is the stock price on day t and ϵ_t is independent, identically distributed. To create the bootstrap sample of returns under this null hypothesis, the actual returns are re-sampled with replacement to generate a new series of 4,820 daily returns for each simulation. Then the bootstrap return series is transformed into the simulated price index series. The initial value of the simulated price series is set at 100 since in the actual data the SET index begins on the first day of trading on the SET. The bootstrap returns are independent and identically distributed, and the simulated price series will have the same drift and unconditional distribution as the actual price series.

The null hypothesis of the AR(1) model requires additional steps to be taken. First, the following null model is estimated from the actual SET returns:

$$r_t = \alpha + \beta * r_{t-1} + \epsilon_t \quad |\beta| < 1$$

where r_t is the return on day t . Under the null hypothesis, innovation, ϵ_t , is assumed to be identically and independently distributed with a mean of zero and finite variance. The estimated residuals, e_t , are standardized by their standard deviations and saved. Second, simulated returns are then projected from the estimated AR(1) model, with the error component being sampled with replacement from the standardized residuals. The actual first day returns from the SET are used as the initial value of the lag endogenous variable in the AR(1) model in order to generate the first simulated returns. Subsequent simulated returns are generated by using lag simulated returns as the lag endogenous variable.

Let $r_{b,t}$ be the bootstrap returns on day t , then

$$r_{b,t} = \alpha + \beta * r_0 + e_{b,t} \quad t=1$$

$$r_{b,t} = \alpha + \beta * r_{b,t-1} + e_{b,t} \quad t=2, \dots, n$$

where $e_{b,t}$ is the error component which is randomly drawn with replacement from the estimated standardized residuals.

V. A. Bootstrapping the Random Walk Model

Table 9 shows the bootstrap results of the random walk model based on 500 simulations.¹⁶ All numbers showed in panel A represent the fraction with values greater than the original SET series, which can be taken as the simulated p-values. For VMA(1,50,0), none of the simulated mean buy returns are as large as those of the SET series, while all the simulated mean sell returns are larger than those of the SET series. The fraction of buy-sell spreads with values greater than the spread from the SET series is zero. The simulated series also has a standard deviation that is too high during buy signals and too low during sell signals. The results lead to a strong rejection of the hypothesis that the random walk model is a return-generating process capable of adequately describing the stochastic process of the SET return series. Other simulations of the VMA follow a similar pattern as VMA(1,50,0).

The TRB results do not lead to as strong a rejection of the null hypothesis as does the VMA, but the outcome remains a rejection at the conventional significance

¹⁶ The simulation of FMA(1,200,0), whose reported p-values are mostly in the intermediate range between 0.00 and 1.00, is selected to test the stability of these results at various iterations. The results are reported in Table 9A in Appendix 2. Except in the case of small samples, such as ten iterations, the results appear to fall within a small range.

level. However, there is evidence that high buy returns can be generated through the application of FMA rules, as indicated by the high p-values under the Buy column in Panel A. As shown in Panel B, with a p-value of .33 for the Buy-Sell column, it can be seen that the random walk model can not be rejected as a plausible return-generating model that yields as high a buy-sell spread as does the actual SET series through the application of the FMA rule. Returns generated by buy and sell signals under the random walk model do not have significantly different variances, no matter what rules are applied, as can be seen in Panel B under the two Std. columns.

Except for the application of the FMA rule, these results, namely the rejection of the random walk model under the application of the VMA and TRB rules, are comparable to those of Brock et al. (1992). Notably, the p-values of the mean and standard deviation in the Buy column are close to 0.00 and 1.00, those in the Sell column are close to 1.00 and 0.00, and those for the buy-sell spread are close to 0.00.

Table 9: Bootstraps of the Random Walk Model

Panel A: Individual Rules (Fraction > SET)						
Rules		Buy	Std.	Sell	Std.	Buy-Sell
(1,50,0)	VMA	0.000	0.996	1.000	0.004	0.000
	FMA	0.864	0.990	0.996	0.000	0.164
	TRB	0.000	0.000	0.994	0.032	0.000
(1,50,0.01)	VMA	0.000	0.850	1.000	0.000	0.000
	FMA	0.908	0.826	0.998	0.506	0.180
	TRB	0.000	0.000	0.782	0.000	0.000
(1,150,0)	VMA	0.000	0.890	1.000	0.136	0.000
	FMA	0.552	0.364	1.000	0.000	0.000
	TRB	0.000	0.000	0.706	0.040	0.002
(1,150,0.01)	VMA	0.000	0.780	0.996	0.058	0.000
	FMA	0.970	0.000	0.572	0.996	0.860
	TRB	0.000	0.000	0.124	0.000	0.088
(1,200,0)	VMA	0.016	0.928	0.988	0.112	0.006
	FMA	0.430	0.298	0.462	0.276	0.538
	TRB	0.000	0.000	0.538	0.044	0.004
(1,200,0.01)	VMA	0.010	0.814	0.996	0.136	0.000
	FMA	0.586	0.958	0.880	0.360	0.234
	TRB	0.000	0.000	0.322	0.010	0.032
Panel B: Aggregate over all Rules						
VMA Fraction>SET		0.00433	0.87633	0.99667	0.07433	0.00100
Mean		0.00054	0.01245	0.00060	0.01243	-0.00006
SET		0.00139	0.01183	-0.00310	0.01363	0.00449
FMA Fraction>SET		0.71833	0.57267	0.81800	0.35633	0.32933
Mean		0.00555	0.03864	0.00496	0.03876	0.00059
SET		0.00151	0.03999	-0.01658	0.04383	0.01809
TRB Fraction>SET		0.00000	0.00000	0.57767	0.02100	0.02100
Mean		0.00513	0.03894	0.00566	0.03858	-0.00053
SET		0.02980	0.07135	0.00461	0.05800	0.02519

In panel B the simulated p-values are averaged across all applications of a particular rule and reported in the row labelled Fraction > SET. The row labelled Mean reports the average of the statistics compiled from 500 simulations, and the row labelled SET shows the corresponding statistics from the actual SET series, similar to the results given in section III. With p-values of .001 and .021 for the buy-sell spread under the VMA and TRB rules, respectively, it can be seen that, for these two technical trading rules, the random walk model is rejected as an appropriate return-generating model. In the Buy-Sell column, the rows labelled Mean show that, had the SET return series followed a random walk process, the average across all variations of the VMA and TRB rules would result in a negative instead of a positive buy-sell spread. Thus, these technical trading rules would not be useful if the SET series were actually a random walk.

Under the VMA rule, the row labelled Mean also reveals that the means and standard deviations of simulated returns during buy signals are very close to those during sell signals, while the row labelled SET reveals large differences between the buy and sell statistics in the actual series. The FMA rules provides a weaker rejection of the random walk model. The average results of the applications of the FMA rule show that 72% of mean buy returns from the simulated random walk series are as large as or larger than those of the SET series. However, the Sell and the Buy-Sell columns show that the random walk model leads these rules to produce mean sell returns that are too high and a buy-sell spread that is too low. The average buy-sell

spread generated by the application of the FMA rules, although positive, is 0.0006, in comparison to 0.0181 when the FMA rule is applied to the actual SET series.

The average results of the VMA and FMA rules under the Sell column show that these rules fail to generate one of the interesting phenomena that results from the actual SET series, namely, negative returns during sell signals. The aggregate results also show that for all three types of rule, the standard deviation of returns varies only marginally during buy and sell signals. This feature also is not seen in the actual SET series.

V. B. Bootstrapping the AR(1) Model

The positive autocorrelation of stock returns may be the cause of an up or down trend detectable by trading rules. The bootstrap of the AR(1) model will test whether this stochastic process can explain the results of the application of trading rules given in section III. The estimated AR(1) model from the SET series is:

$$r_t = 0.000398 + 0.226991 * r_{t-1}$$

$$(0.000183) \quad (0.014825)$$

$$R^2=0.051$$

where the standard errors are showed in parentheses. The coefficient on the lagged return is highly significant, and the intercept is significant at a conventional level.

Table 10 shows the bootstrap results of the application of trading rules under the hypothesis of the AR(1) model, based on 500 simulations. These results differ markedly from those under the null hypothesis of the random walk model. In Table 10 many of the simulated p-values are large, thus the possibility that the AR(1) model

may account for the results seen from the application of trading rules under traditional simulations is not rejected. As seen in the last column of panel A, many rules can generate a buy-sell spread as large as that of the actual SET, with p-values close to 1.00. These results are also in contrast to the findings of Brock et al. (1992), who note that the simulated AR(1) process generates p-values of close to 0.00 for most of the buy-sell spreads seen on the U.S. stock market. It is interesting that a stronger serial correlation exists for daily returns on the SET than on the U.S. market. The sample statistics in Table 1B give a first-order autocorrelation of 0.227 for the SET series, in comparison with 0.033 in the Brock et al. sample. Panel B of Table 10 reveals other interesting results that differ from the simulated random walk process. The average statistics show that, for the VMA and FMA rules, the AR(1) model can generate the negative returns seen in the actual SET series during sell signals. For the VMA rule, the standard deviation of high mean buy returns is lower than that of low mean sell returns. However, for all aggregate simulated AR(1) results, the mean buy returns are too high and the mean sell returns too low in comparison with the results from the actual SET series. Thus, the buy-sell spreads from the simulated series are much too large. As well, the magnitude of the simulation results presents a picture that does not closely resemble the actual series.

Table 10: Bootstraps of the AR(1) Model

Panel A: Individual Rules (Fraction > SET)						
Rules		Buy	Std.	Sell	Std.	Buy-Sell
(1,50,0)	VMA	0.994	1.000	0.058	1.000	1.000
	FMA	0.552	1.000	0.450	1.000	0.608
	TRB	0.814	1.000	0.124	1.000	0.926
(1,50,0.01)	VMA	0.992	1.000	0.028	1.000	1.000
	FMA	0.594	1.000	0.392	1.000	0.624
	TRB	0.836	1.000	0.110	1.000	0.944
(1,150,0)	VMA	0.944	1.000	0.164	1.000	0.968
	FMA	0.562	1.000	0.436	1.000	0.594
	TRB	0.756	1.000	0.212	1.000	0.844
(1,150,0.01)	VMA	0.944	1.000	0.206	1.000	0.972
	FMA	0.554	1.000	0.414	1.000	0.590
	TRB	0.784	1.000	0.188	1.000	0.882
(1,200,0)	VMA	0.940	1.000	0.206	1.000	0.964
	FMA	0.540	1.000	0.402	1.000	0.628
	TRB	0.748	1.000	0.184	1.000	0.844
(1,200,0.01)	VMA	0.926	1.000	0.234	1.000	0.942
	FMA	0.414	1.000	0.376	1.000	0.630
	TRB	0.756	1.000	0.236	1.000	0.850
Panel B: Averages over all Rules						
VMA Fraction>SET		0.95667	1.00000	0.14933	1.00000	0.97433
Mean		0.06115	1.02545	-0.02253	1.02620	0.08368
SET		0.00139	0.01183	-0.00052	0.01363	0.00191
FMA Fraction>SET		0.53600	1.00000	0.41167	1.00000	0.61233
Mean		0.10648	3.96822	-0.17201	3.93237	0.27849
SET		0.00151	0.39990	-0.00592	0.04383	0.00743
TRB Fraction>SET		0.78233	1.00000	0.17567	1.00000	0.88167
Mean		0.42372	4.00270	-0.45483	3.99538	0.87855
SET		0.02980	0.07135	0.00461	0.05800	0.02519

VI. Monte Carlo Simulation of the Markov Process

An interesting characteristic of trading rules is that they separate the return series into two groups: those generated following buy and sell signals. This section tests the hypothesis that profits resulting from the application of trading rules are plausible when stock returns are generated by a mixed distribution process, with different means and variances. The null model is a two-state Markov-chain model, and the testing strategy is similar to the bootstrapping simulation done in the previous section. However, the Markov-chain null model is completely specified with a normality assumption for error distribution, thus the test is a Monte Carlo simulation.

VI A. Markov Model with Observable States

The simple question to be tested first is whether profits generated through the application of trading rules are greater than average returns because the actual stock returns are generated by two distributions corresponding to returns greater than and less than mean returns. For this null model, the mean of the series is chosen as the criterion used to separate individual realizations of returns between one of two discrete, mutually exclusive and collectively exhaustive states. Thus for each observation the corresponding state is

$$S_t = \begin{cases} 0 & \text{if } r_t < \bar{r} \\ 1 & \text{if } r_t > \bar{r} \end{cases}$$

where r_t and $\bar{r}$ are returns at time t and the mean of the SET series, respectively. The two-state Markov-chain model can be expressed as

$$r_t = (\mu_0 + \mu_1 S_t) + (\alpha_0 + \alpha_1 S_t) z_t$$

$$p_{00} = p(S_t=0|S_{t-1}=0) = p$$

$$p_{01} = p(S_t=1|S_{t-1}=0) = 1-p$$

$$p_{11} = p(S_t=1|S_{t-1}=1) = q$$

$$p_{10} = p(S_t=0|S_{t-1}=1) = 1-q$$

$$z_t \sim N(0,1).$$

This model can generate different means and variances for returns under the two states. In state 0, returns are generated from the distribution with mean μ_0 and variance α_0 while in state 1, the mean is $\mu_0 + \mu_1$ and the variance is $\alpha_0 + \alpha_1$. Since the probability that determines the current state and the governing distribution from which returns are generated depend only on the state of the last period, this is a two-state first-order Markov chain. The set of transitional probabilities that must be inferred from the data is assumed to be constant over time; in other words, stationarity of the Markov chain is assumed.

McQueen and Thorley (1991) show that if the sample is long enough for the initial state to be ignored in calculating conditional probabilities in the transitional matrix, then the inferred transitional probabilities that maximize a likelihood function are simply the sample conditional probabilities. In this study, the transitional count matrix represents the categorization of data in the sample, and the following notation is used for the transitional count and transitional probability matrices:

Transition Count Matrix
Previous Current State
States 0 1

0	N00	N01
1	N10	N11

Transition Probability Matrix
Previous Current State
States 0 1

0	p00	p01
1	p10	p11

For example, N01 is the number of realization in the sample where the previous state is 0 and the current state is 1. The log likelihood function of the state process is:

$$L(S_t, \Lambda, \pi) = \log(\pi) + \sum_{i=0}^1 N_{i0} \log(p_{i0}) + N_{i1} \log(1 - p_{i0})$$

Where Λ is a vector of parameter [p00, p10] and π is the probability of an initial state.

The first partial derivative of this likelihood function is:

$$\frac{\partial \log L}{\partial p_{i0}} = \frac{\partial \log \pi}{\partial p_{i0}} + \frac{N_{i0}}{p_{i0}} + \frac{N_{i1}}{(1 - p_{i0})}$$

Setting this derivative to zero results in the following expression for p_{i0} :

$$p_{i0} = \frac{N_{i0}}{N_{i0} + N_{i1}} + \frac{\partial \log \pi}{\partial p_{i0}} * \frac{p_{i0} * (1 - p_{i0})}{N_{i0} + N_{i1}}$$

Note that as $N_{i0} + N_{i1}$ increases the second term in the expression decreases in importance and the information about the initial state can be ignored, thus p_{i0} can be approximated by the first term of the expression. McQueen and Thorley show that their sample, at annual and weekly frequencies from 1947 to 1987, justifies this

approximation. This paper uses the same method in calculating transitional probabilities.

In order to simulate the Markov process, however, the initial state is required. Duffie and Singleton (1993) point out that even if the transitional function of the Markov process is stationary, the simulated process is not generally stationary if the initial state is arbitrarily selected rather than drawn from the ergodic distribution of the process. Thus, the unconditional probability that the initial state will be 0 or 1, which is a nonlinear function of all transitional probabilities of the process, is derived as follows.¹⁷ The unconditional probability that the state in period 1 will be 0 can be expressed as the sum of the products of the unconditional probability of the initial state and the conditional probability of the first state:

$$p(S_1=0) = p(S_1=0|S_0=0)*p(S_0=0) + p(S_1=0|S_0=1)*p(S_0=1)$$

It follows that the system of equations to be solved is

$$\pi_0 = p_{00}*\pi_0 + p_{10}*\pi_1 \quad (1a)$$

$$\pi_1 = p_{01}*\pi_0 + p_{11}*\pi_1 \quad (2a)$$

$$\pi_0 + \pi_1 = 1 \quad (3a)$$

Using (3a) to derive out the expression of π_1 in (1a) and (2a) gives the following results:

$$\pi_0 = p_{00}*\pi_0 + p_{10}(1-\pi_0) \quad (1b)$$

$$(1-\pi_0) = p_{01}*\pi_0 + p_{11}(1-\pi_0) \quad (2b)$$

¹⁷ An alternative method is to select an initial state arbitrarily and then discard the first N results of the simulated series, assuming that the process converges quickly to its stationary distribution before or at N. This may not be an economical alternative for large numbers of repeating simulations.

Use (2b) in (1b) gives

$$\pi_0 = p_{00} \pi_0 + p_{10} p_{01} \pi_0 + p_{10} p_{11} - p_{01} p_{11} \pi_0$$

$$\pi_0 = \frac{p_{10} p_{11}}{p_{10} p_{11} + (1 - p_{00}) - p_{10} p_{01}}$$

The application of trading rules to the simulated Markov process is done as follows. First, the simulated state series is generated by using an unconditional probability for the initial state and then using the transitional probabilities for successive states. Second, a simulated return series is generated using the simulated state series together with the parameters of the Markov chain model and a random drawing from standard Gaussian distribution for z_t . The trading rules are then applied to the simulated return series, the appropriate statistics are calculated, and the three steps are repeated until 500 simulations have been completed.

The transitional count matrix and the transitional probability matrix for the original SET series are shown below.

Transition Count Matrix
Previous States Current State
 0 1

0	1342	871
1	871	1185

Transition Probability Matrix
Previous States Current State
 0 1

0	0.6064	0.3936
1	0.4236	0.5764

The transitional probability matrix shows some persistence for returns to remain in state 0 in the current period when the previous state is 0. The expected duration for being in state 0 is $(1-p_{00})^{-1}$, or 2.54 days. There is less persistence for remaining in state 1 in the current period when the previous state is 1. The probability of the initial state being 0 is 0.5184.¹⁸ When states are 0 the mean and variance of returns are -0.0066 and 0.0102; when states are 1 the mean and variance are 0.0081 and 0.0005. It turns out that the means of the two distributions differ markedly: one is negative and the other positive. In addition, the distribution with the higher mean has a lower variance, thus there is a good possibility that this null model can explain the results deriving from the application of trading rules.

VI B. The Simulated Markov Model

Table 11 shows the results of applying trading rules to the simulated Markov model under the described null hypothesis, based on 500 simulations. The results are similar to the bootstrapping of the random walk model in the sense that, except for the FMA

¹⁸ In fact, the sample used is quite large, and the unconditional probability of the initial state being 0 based on counting the realizations in the sample is practically the same as this calculated probability. When counting, $p_0 = 2213/4270 = 0.5183$.

rules, the null model is rejected at a conventional level. In Panel A, under the Buy-Sell column, many figures of zero or close to zero show that this class of the Markov model fails to generate a buy-sell spread as large as the original SET series. In Panel B, under the Sell column, the simulated mean sell results from the VMA and FMA rules are still positive, in contrast to the negative value in the original SET series, despite the fact that the distribution that generates the below-mean returns for the simulated Markov model has a negative mean. Also in Panel B, the standard deviation of returns generated during buy and sell signals, based on the application of trading rules, are very close, although the high-return and low-return distributions under the null hypothesis have drastically different standard deviations.

Table 11: Trading Rule and the Simulated Markov Model with Observable States

Panel A: Individual Rules (Fraction > SET)						
Rules		Buy	Std.	Sell	Std.	Buy-Sell
(1, 50, 0)	VMA	0.000	0.000	1.000	0.000	0.000
	FMA	0.874	0.984	0.992	0.000	0.130
	TRB	0.000	0.000	0.996	0.000	0.000
(1, 50, 0.01)	VMA	0.000	0.000	1.000	0.000	0.000
	FMA	0.920	0.606	0.998	0.204	0.166
	TRB	0.002	0.000	0.610	0.000	0.002
(1, 150, 0)	VMA	0.000	0.000	0.996	0.000	0.000
	FMA	0.422	0.150	1.000	0.000	0.000
	TRB	0.000	0.000	0.596	0.000	0.002
(1, 150, 0.01)	VMA	0.000	0.000	0.998	0.000	0.000
	FMA	0.974	0.000	0.556	0.994	0.898
	TRB	0.008	0.000	0.066	0.000	0.154
(1, 200, 0)	VMA	0.008	0.000	0.950	0.000	0.004
	FMA	0.450	0.116	0.446	0.070	0.514
	TRB	0.000	0.000	0.434	0.008	0.008
(1, 200, 0.01)	VMA	0.000	0.000	0.952	0.000	0.000
	FMA	0.600	0.976	0.928	0.164	0.208
	TRB	0.004	0.000	0.288	0.004	0.074
Panel B: Averages over all Rules						
VMA Fraction>SET		0.00133	0.00000	0.98267	0.00000	0.00067
Mean		0.00058	0.01211	0.00031	0.01044	0.00027
SET		0.00139	0.01183	-0.00052	0.01363	0.00191
FMA Fraction>SET		0.71667	0.47200	0.82000	0.23867	0.31933
Mean		0.00522	0.03577	0.00451	0.03585	0.00071
SET		0.00151	0.39990	-0.00592	0.04383	0.00743
TRB Fraction>SET		0.00233	0.00000	0.49833	0.00200	0.04000
Mean		0.00467	0.03556	0.00354	0.03538	0.00113
SET		0.02980	0.07135	0.00461	0.05800	0.02519

VII. Conclusion

This paper produces three main findings. First, some interesting stochastic properties of the return series on the SET can be discovered from trading rules. According to signals generated by the application of trading rules, returns have a high mean during buy signals and a low or negative mean during sell signals; both are statistically different from the sample mean. Moreover, despite the higher mean, returns during buy signals have a lower standard deviation than those obtained during sell signals. This characteristic contradicts conventional thinking, which believes that higher returns are associated with a higher level of risk. Of three types of trading rules, namely VMA, FMA and TRB, the former (VMA) is more useful than the others when applied to the SET index.

Second, profits resulting from the application of trading rules are economically significant. Incorporating signals generated by the VMA rule into long/short and timing strategies demonstrates that trading rule profits are higher than those produced by a buy-and hold strategy, even over a short horizon and even at higher-than-normal transaction costs.

Third, the stochastic properties of the SET return series that are discovered by trading rules cannot be adequately explained by a random walk model or a Markov-chain model. Thus, using trading rule profits as the criterion, these models are rejected as the true return-generating processes for the SET data. The autoregressive model of order one has the potential to explain some qualitative characteristics of trading rule profits but does not satisfactorily capture the quantitative aspects. This

evidence indicates that trading rules are capable of capturing special characteristics of stock return series that are difficult for this set of stock return models to represent.

Many possibilities exist for extending this research. To increase coverage, the tests used in this paper can be applied to many other trading rules and existing stock return models. To pursue the issue of the economic significance of profits, the next step is to apply trading rules to individual stocks or small portfolios. This calls for a large database of all individual stock prices since the inception of the SET, but the advantage is that investors will not have to rely on the availability of a product that tracks the SET index in order for the rules to work. The result will be directly applicable to small investors who do not usually hold large and highly diversified portfolios. A small, dynamic portfolio can be created and the composition of stocks in the portfolio continuously changed in accordance with stock selection criteria derived from the use of trading rules. Randomization tests will be needed to verify that the profits generated by a trading rule portfolio are not merely the product of chance. This can be done by comparing the trading rule-generated profits to those obtained by a large number of portfolios whose composition is continuously updated by random selection.

The section on the Markov-chain process suggests another area for further research. The Markov model used in this paper assumes that states are observable based on subjective criteria used by the researcher. Although intuitive criteria are selected, much information can be lost by imposing this structure on the data. A statistical model of the Markov process that is superior in describing the stochastic

properties of returns from the SET can be achieved by designing an estimation procedure for the model in which states are not observable by researchers *ex ante*. The unobservable states will be matched to observations within the parameter-estimation process, such that the likelihood function of the return-generating process is maximized; in other words, the criterion for classifying the state is endogenously selected. The Markov model has many interesting features that can be used to investigate the stochastic properties of stock returns, both by itself as well as in combination with trading rule simulations.

Appendix 1

Table 4A: Test Results for the Fixed-Length (Five-Day) Moving Average (FMA) Rules

Test	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	40	44	-0.0038 (-1.9740)	-0.0088 (-1.5195)	0.5000	0.4773	0.0049 (0.6179)
(1,50,0.01)	71	49	-0.0020 (-1.6615)	-0.0084 (-3.1132)	0.4648	0.3673	0.0064 (1.5578)
(1,150,0)	24	23	0.0028 (0.0373)	-0.0095 (-1.7726)	0.3750	0.3043	0.0123 (1.2681)
(1,150,0.01)	31	31	0.0008 (-0.3027)	-0.0012 (-0.6409)	0.5161	0.4516	0.0020 (0.2592)
(5,150,0)	17	18	0.0007 (-0.4195)	-0.0221 (-1.6367)	0.5882	0.5000	0.0227 (1.4530)
(5,150,0.01)	17	22	0.0059 (0.7694)	-0.0023 (-0.7053)	0.7059	0.5455	0.0082 (0.8960)
(1,200,0)	21	23	-0.0160 (-1.8682)	0.0075 (1.1454)	0.4286	0.6087	-0.0235 (-2.1920)
(1,200,0.01)	38	25	-0.0001 (-0.5028)	0.0011 (0.2300)	0.5526	0.5600	-0.0012 (-0.1461)
(2,200,0)	19	22	-0.0121 (-1.9556)	0.0074 (0.7059)	0.3684	0.5000	-0.0195 (-1.8178)
(2,200,0.01)	31	23	0.0038 (0.2167)	0.0089 (0.6535)	0.5806	0.6087	-0.0050 (-0.4737)
Average			-0.0020	-0.0027			0.0007

Note: Rules are represented as (short moving average, long moving average, band).

N(Buy) and N(Sell) are the number of signals generated.

Buy and Sell are the mean returns accumulated over five-day periods after each signal; the corresponding t-ratios (in parentheses) test the difference between these returns and the unconditional nonoverlapping five-day mean.

Buy>0 and Sell>0 are the proportion of returns greater than zero.

Buy-Sell is the difference between mean buy and mean sell returns; the corresponding t-ratios (in parentheses) test the difference between these returns and zero.

Appendix 2

Table 9A: Convergence of Fractile Statistics from the Bootstraps of the Random Walk Model

No. Simulations	FMA(1,200,0) (Fraction > SET)				
	Buy	Std.	Sell	Std.	Buy-Sell
10	0.500	0.100	0.600	0.300	0.600
50	0.460	0.240	0.480	0.220	0.500
100	0.450	0.380	0.500	0.230	0.450
500	0.430	0.298	0.462	0.276	0.538
1000	0.427	0.310	0.471	0.247	0.479
1500	0.425	0.301	0.458	0.288	0.515
2000	0.446	0.295	0.473	0.268	0.499
2500	0.458	0.301	0.455	0.274	0.498
3000	0.431	0.297	0.453	0.277	0.502
4000	0.456	0.306	0.465	0.276	0.507
5000	0.475	0.288	0.465	0.266	0.521

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III: Relationship between Daily Returns, Volatility, and Trading Volume in the Markov Switching Model of Stock Returns.

The Relationship between Daily Returns, Volatility, and Trading Volume in the Markov Switching Model of Stock Returns.

I. Introduction

The empirical relationship between stock prices, volatility and trading volume has been actively studied; however, current knowledge of the theoretical relationship between them is still evolving and far from complete. Trade volume has no important role to play in conventional asset pricing models, which maintain the assumption of there being a complete asset market and homogenous traders. Many recent models relax this limitation and, as a result, find that trade volume affects both stock prices and future expected returns, usually in a complicated way. The theoretical models of the relationship between stock price and trade volume can be divided into two groups: those based on competitive trading, in which a large number of agents are active on the market, and those based on noncompetitive trading, in which a few agents engage in strategic trading. Within the competitive trading models, the motivation for stock trading has been postulated to arise from any of various sources of heterogeneity among traders, such as asymmetric information, difference in beliefs, and different preferences or constraints. Karpoff (1987) discusses some earlier models, notably the Sequential Information Arrival model by Copeland (1976), that use heterogenous information between traders to propose a role for trade volume in the

Special thanks to Simon van Norden, of the Bank of Canada, who generously provided the algorithm and documentation for the Gauss procedure for the Markov switching estimation, and to Brian Erard for help in solving various problems during the estimation.

pricing of stocks. Wang (1994) lists more recent models in this area, many of which rely on noninformational trading of noise traders, whose fluctuations in demand are exogenously given. Wang's model allows traders to differ both in the information they possess about stock fundamentals and in private real investment opportunities. This allows noninformational trading to be endogenized into a rational optimizing behaviour. Brock and LeBaron (1993) provide an alternate model in which the connection between volume and price does not necessarily come from the external demands of liquidity traders, but can result from the trading process itself. In their model, traders function as agents who adapt their trading strategy on a time scale that overlaps with the timing of the trading process. These new theoretical models show that the relationship between price and trading volume is not straightforward. It can differ between models, as well as within a single model, depending on the mechanisms that drive trading and how they are modelled.

On the empirical side, Karpoff's (1987) survey of the literature on the relationship between price changes and trading volume summarizes two stylized facts that had emerged up to that point. First, a positive relationship exists between volume and the absolute value of the price change. Second, there is a positive correlation between volume and price change per se. Karpoff attributes these contradicting stylized facts and the weak statistical significance of the findings to a misspecification caused by imposing a linear relationship between volume and price. Gallant, Rossi, and Tauchen (1992) carried out a comprehensive study of the dynamics among price change, volatility, and volume using daily index and volume data from the New York

Stock Exchange during 1928 to 1987. They report four empirical regularities: firstly, a positive correlation exists between conditional volatility and volume, but the direction of price change is unrelated to contemporaneous volume; secondly, high volumes follow large price changes; thirdly, the asymmetry of conditional variance, or the "leverage" effect,¹ decreases when returns are conditional on lagged volume, and; fourthly, a positive conditional mean-variance relationship exists when volume is introduced into the analysis. This set of stylized facts is the result of a nonparametric estimation of the conditional density of the price change and volume data.²

A recent parametric study showing that richer information about the price process can be gathered when volume is taken into account is Lamoureux and Lastrapes (1990). They use trading volume as a proxy for information flow to the market and enter it into the variance equation of the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. They find a positive and significant relationship between daily return variance and volume, and that the ARCH effect disappears.

Subsequently, other economists have examined the connection between volume and persistence in variance and the autocorrelation of stock returns. Brock and

¹ The leverage effect is often referred to as an asymmetric response of conditional variance to negative and positive stock returns.

² The advantage of using a nonparametric approach to study the joint processes of price and volume is the avoidance of misspecification errors. Other studies, which focus on the marginal process of price and assume volume to be exogenous, are subject to misspecification errors if volume is instead endogenous. However, according to the definition set out in Engle, Hendry, and Richard (1982), valid estimations of the specific parameter of the price process would require volume to be only weakly endogenous (see also the discussion in Ericsson (1992)).

Lebaron (1993) find that simulations done using their adaptive agent model match many empirical moments of volatility and volume of stock returns. Lebaron (1993) suggests that shocks to volume can be amplified by the trading process over several days, and that the volatility-volume dynamic is asymmetric. When volume is high relative to its long term average, the relationship is negative; on the other hand, when volume is low, the relationship is positive. Campbell, Grossman, and Wang (1993) find that volume has a negative effect on the autocorrelation of stock returns. Lebaron (1992) discovers a similar effect using the measure of volume relative to its long period average, but he finds an opposite, positive effect on autocorrelation using the measure of volume relative to its recent period average.

This paper examines the relationship between stock returns, volatility, and volume in the Markov Switching model of stock returns. In this framework, stock returns are generated from a mixture of distributions that differ in mean or variance or both. Each of these distributions represents a distinct state of the stock market. The Markovian structure governs the transitional probability of stock market switches between different states through time.

The Markov model offers many opportunities to examine the stochastic properties of time series in a nonstationary framework and has been used to explore many new and interesting questions. For example, Hamilton (1989) is a pioneering paper that describes the stochastic process of real GNP in the postwar U.S. as one of switching between two regimes of positive and negative growth rates. McQueen and Thorley (1991) use a Markov chain model to reject the random walk hypothesis of

stock returns. McQueen and Thorley (1993) find asymmetry in business cycles, specifically that the transitional probability of moving from contraction to recovery is higher than that of moving from recovery to contraction.

In an earlier attempt to fit the Markov model to the variance of returns, Pagan and Schwert (1990) suggest that ARCH and GARCH specifications are inadequate to account for nonstationarities in variance.³ Recently, after considerable research on return variance using various ARCH techniques, there has been increasing interest in exploring the issue using the Markov Switching specification. It has been observed that the ARCH specification is inadequate to explain the short-lived jump in variance, and that Markov Switching may better fit the pattern of jump and persistent variance that coexist in the data. This new type of modelling, known as Markov Switching Autoregressive Conditional Heteroscedasticity (SWARCH), is introduced in Hamilton and Susmel (1993) and used in Kim (1993) and in Kim and Kim (1993). However, these Markov models are univariate and have not explored any economic variables that might interact with stock returns within the Markov structure. Van Norden and Schaller (1993) innovate in using a multivariate specification, and especially by allowing economic variables to affect transitional probabilities; they find an asymmetric response of returns and transitional probabilities to past price-dividend ratios in monthly data from the U.S. This paper uses the van Norden and Schaller (1993) multivariate specification, and it complements both the literature on volume and that on the Markov Switching model of daily stock returns by considering the role

³ Pagan and Schwert (1990) use a two-stage variance estimation process. Firstly, a chosen measure of variance is calculated; then the variance series is fitted to various statistical models.

of trading volume in the Markov model. Volume is one of the economic variables that may be very important to an understanding of the nature of stock returns at high frequency, and the Markov model so far appears to be a promising statistical model that does well in capturing many features of stock return data.

This paper addresses two questions. Firstly, when the return process is modelled using the Markov switching model, what is the relationship between returns and volume? Secondly, what is the magnitude or extent of the effect of volume on the variation of transitional probabilities through time? Estimations reveal five interesting results. Firstly, in the context of a two-state Markov switching model, stock returns in Thailand are driven by the process of two switching regimes with different variances, one of which is much larger than the other. These two regimes represent the high variance state and the low variance state of the stock market. Secondly, although the average mean returns in these two regimes are very close, changes in contemporaneous volume can cause a substantial difference between them. Volume is positively related to stock returns in both regimes; however, the effect of volume on returns is much larger if the stock market is in the high variance state than if it is in the low variance state. The effect of volume on expected returns is independent of the ability of volume to affect transitional probabilities of regimes. Thirdly, lag volume is positively related to the next period's returns. One standard deviation increase in lag volume adds one third the size of the next period's expected returns, or up to one half when the lag volume measured relative to its local trend is used. Fourthly, contemporaneous volumes have significant but opposite effects on the persistence probabilities of

regimes. An increase in volume decreases the chance that a low variance state will continue but increases the chance that a high variance state will be prolonged. Lag volume has a weak effect on the probability of persistence of state, but the effect is statistically stronger when relative volume measure is used. Fifthly, unlike many other experiences in the literature, which find that a fast-moving measure of volume is uninformative or renders weak results, the Markov switching model reveals many interesting relationships using the daily growth rate of volume. Some results are statistically stronger with this measure of volume than with volume relative to its slow-moving trend.

The structure of the paper is as follows: Section II describes the data and their transformation. Section III describes the statistical models of the Markov switching process and informally discusses why this model was chosen. Section IV presents and discusses the estimation results. Section V summarizes the findings and suggests areas for further research.

II. Daily Returns, Volatility, and Volume in the SET

The data used are from the Thailand database of the Pacific-Basin Capital Markets (PACAP) Research Center⁴ and cover the period from April 30, 1975, to December 30, 1992. The series chosen to represent daily returns is the value-weighted market returns with all cash dividends reinvested. Trade volume is the total number of shares

⁴ Pacific-Basin Capital Markets (PACAP) Research Center, College of Business Administration, The University of Rhode Island.

traded for all stocks over the course of each trading day.⁵ Volatility is the variance of daily return, which is calculated as follows:

$$\sigma_t^2 = (r_t - \mu)^2$$

where r_t is the daily return at time t , and μ is the mean of daily returns over the sample period. The summary statistics of series used in this paper are provided in Table 1.

Figure 1 gives the plot of daily returns. The return series shows no trend. Returns in the middle of the series appear less volatile than those at the beginning and at the end. Figure 2 shows the daily trading volume. The volume shows a continuous upward trend although, owing to a large difference between trading volumes at the beginning and during the recent period of the Thai stock market, the earlier trend does not show up in the figure. In 1976, the first full year of trading on the SET, the average daily trading volume is 20,251 shares. In 1992, the last year of the sample, the trading volume increases to an average of 107,911,000 shares per day. A dramatic increase in trading volume near the end of the sample is clearly visible from the figure. In studying the relationship between returns and volumes at high frequency, the long-term trend in volume will interfere with the short-run relationship under analysis and must be removed. Using a turnover ratio, which is the ratio between trading volume and outstanding shares, reduces the trend but usually not enough to make the series stationary. Researchers employ various transformations to obtain a stationary volume series, for example fitting an exponential trend to log volume

⁵ These series are in the Daily Market Return File and are labelled DVRMWD and TRDVOL.

(Gallent, Rossi and Tauchen, 1992), or using a deviation from past moving averages (LeBaron, 1992). This paper uses the growth rate of the trading volume from the previous trading day as a volume measure.⁶ The growth rate is calculated as a log first difference of the volume series and is plotted in Figure 3. In this figure, the series looks more stationary, with a mean close to zero. For ease of interpretation, the series is normalised to have a sample variance of one for use in estimations. Without any prior knowledge about an analytical model of the relationship between returns and trading volume in a Markov model, this first volume measure appears logical, since the transitional probability in the econometric specification, which will be described in the following section, follows a Markov process of order one, thus the measure of volume is also specified relative to the previous period. An alternative transformation will be tried later. Figure 4 shows the daily variance of returns. This figure reveals two clusters of relatively high variances, one at the beginning and one at the end of the series, in comparison with the lower variances in the middle of the series. The mixture of relatively high and low variances is punctuated by two extraordinarily high variances, the first of which occurred on September 9, 1975, and the second on May 28, 1979.⁷

⁶ In some cases the empirical results are sensitive to the method of transformation. An alternative transformation is tried in section IV B.

⁷ Three variance regimes may exist, namely, high, low, and extraordinarily high. The latter would accounts for these two variances; a formal specification test may be warranted to determine whether these data can reach the third variance regime. Bonomo and Garcia (1994) show that imposing a misspecified Markov structure to the data gives misleading results.

III. Markov Switching Model

The two-state Markov switching model describes the series of returns as coming from two distributions, each of which represents a distinct market state. The transitional probabilities that determine each day's prevailing market state have a Markov structure and can generally be represented using the following equations:

$$r_t = \mu_0(1-S_t) + \mu_1 S_t + [\alpha_0(1-S_t) + \alpha_1 S_t] \varepsilon_t \quad (1)$$

$$\begin{aligned} p_{00} &= p(S_t=0|S_{t-1}=0) = p \\ p_{01} &= p(S_t=1|S_{t-1}=0) = 1-p \\ p_{11} &= p(S_t=1|S_{t-1}=1) = q \\ p_{10} &= p(S_t=0|S_{t-1}=1) = 1-q \\ \varepsilon_t &\sim N(0,1) \end{aligned}$$

where S_t indicates which state describes the stock market at time t ; it takes a value of 0 or 1. This model can generate a different mean and variance for returns under the two states. In state 0, the returns are generated from the distribution with mean μ_0 and variance α_0^2 , while in state 1, the mean is μ_1 and the variance is α_1^2 . Since the probability that determines the current state and the governing distribution from which returns are generated (p_{ij} ; $i, j=0,1$) depends only on the state in the previous period, this is a two-state first-order Markov switching model. The states are not observable, and the set of transitional probabilities must be inferred from the data together with other coefficients of the model in the estimation process.

In order to study the influence of trading volume in the switching model, trading volume is allowed to affect two aspects of the specification. Firstly, it can

affect the mean of returns in the two distributions. This leads to the following multivariate specification of the switching model:

$$r_t = \mu_0(1-S_t) + \beta_0 V_t(1-S_t) + \mu_1 S_t + \beta_1 V_t S_t + [\alpha_0(1-S_t) + \alpha_1 S_t] \varepsilon_t \quad (2)$$

Secondly, transitional probabilities can vary in each period in such a way that they depend on trading volume. This leads to the model of time-varying transitional probabilities in which the transitional probability equations have the following specification:

$$\begin{aligned} p_{00} &= p(S_t=0|S_{t-1}=0) = p(V_t) \\ p_{11} &= p(S_t=1|S_{t-1}=1) = q(V_t) \\ p &= \Phi(\gamma_{p0} + \gamma_{pv} V_t) \\ q &= \Phi(\gamma_{q0} + \gamma_{qv} V_t) \end{aligned} \quad (3)$$

where Φ is the standard normal cumulative density function. As usual, p_{01} and p_{10} are equal to $1-p$ and $1-q$, respectively. Models with contemporaneous trading volumes or lag volumes are estimated in order to examine the dynamics of the relationship between returns and trading volume.

Before proceeding to estimations using the Markov switching model in equation (1), two simpler versions of a univariate switching model are estimated. The estimated coefficients of these models will be used as the starting value of parameters in later estimations of the multivariate Markov model, where the interaction between returns and volume is studied. The two models estimated are a normal mixture model:

$$r_t = \mu_0(1-S_t) + \mu_1 S_t + [\alpha_0(1-S_t) + \alpha_1 S_t] \varepsilon_t \quad (4)$$

and a volatility regimes model:

$$r_t = \mu_0 + [\alpha_0(1-S_t) + \alpha_1 S_t] \varepsilon_t \quad (5)$$

where, in both models, $S_t = 0,1$
 $p_0 = p(S_t=0) = p$
 $p_1 = p(S_t=1) = 1-p.$

The normal mixture model is a simple mixture of two normal distributions that differ in both mean and variance. The volatility regimes model is a random walk with heteroscedastic variances coming from two variance regimes. The difference between the normal mixture model and the univariate Markov switching model in equation (1) is that the probabilities of the current state in the normal mixture model are independent of the realised state in the previous period. The variance regimes model is a restricted version of the normal mixture model, where μ_1 is restricted to equalling μ_0 .

The Markov switching model is appealing for many reasons in the context of the relationship between volume and returns. Firstly, both previous empirical results and new analytical models indicate the existence of a complex relationship between volume and returns. There can be more than one relationship between them, and the observed relationship will depend on which mechanism is operating. The effect of volume on returns may be asymmetric, for example, the relationship of volume to low returns may not be the same as to high returns. These asymmetries can be captured by allowing the relationship between volume and returns to differ in different regimes. Secondly, the switching regime also enables the model to account for one regime that

describes the normal state of the stock market, while allowing for the periodic operation of an alternative, special event regime. Looking back over a long history, this special event appears to be a recurrent phenomenon, such as documented in Kindleberger (1978). Friedman and Laibson (1989) emphasize the importance of accounting for extraordinary events in the stock market since these events, although relatively infrequent, can have an important effect on the stock market and the economy. As Gallant, Rossi and Tauchen (1992) observe, volume may play a special role on the days on which these special events occur.⁸ Recent analytical models have generally attempted to modify the former model, which had no meaningful reason for stock trade and therefore no role for volume, so as to incorporate the fundamental relationship between volume and returns. However, the actual data may result from both a general relationship of this type, such as trade between informed and uninformed traders, and from those other times when the relationship between volume and returns is governed by fad, herd behaviour, or panic. The Markov switching model can sort out the observed returns and relate them to competing models such as those presented in van Norden and Schaller (1992).

IV. Estimation Results

Tables 2 and 3 report various univariate models of returns. These models examine the characteristics of regime switching in the return series alone. In this paper, the

⁸ "On Black Monday II (October 19, 1987), the S&P 500 composite index plunged 22.9 percent on the second highest volume ever recorded (604 million shares)." Gallant, Rossi and Tauchen (1992), 199.

estimated coefficients are reported in the tables with their corresponding standard deviations in parenthesis immediately below.

Table 2 shows the estimated results of the two simple switching models, namely, the normal mixture model and the variance regimes model, in columns 1 and 2 respectively. Both these models follow a rather simple switching process, where the probabilities that the observed data come from a specific regime remain the same in all periods, and the sum of probabilities over the two alternative regimes equals one. The first insight about switching regimes in the return series that can be seen from this table is that the variance of returns in one regime is much larger than in the other. Furthermore, in each period, the probability that the stock market will be in the low variance regime, p_0 , is higher than the probability of its being in the high variance regime. This probability is calculated from Table 2 to be approximately 0.828.⁹ Another interesting observation is that, in the specification allowing two regimes to have different means, both means are close together and only one is statistically different from zero.

Two specifications of the univariate Markov switching model, similar to equation (1), are estimated, and the results are reported in Table 3. The specification in the first column allows switching in both mean and variance, while the second column allows switching in variance only. For these two models, the probabilities of state have a Markov structure with a memory of one period. Thus, the probability that the stock market will be in a specific regime in the current period will depend on

⁹ This is the cumulative density value of a normal distribution, which corresponds to the estimated coefficient γ_{p0} reported in the table.

which regime governed the stock market during the previous period. The sum of the probabilities that the stock market will move from one regime in the previous period to another alternative regime in the current period and that it will stay in the same regime equals one. Again, the means of returns in the two regimes are very close and fall within the standard deviation of the estimate for each parameter. Therefore, allowing or disallowing switching in means makes little difference as to how the model fits the data. This point is illustrated by the fact that these two models have identical values of log-likelihood.

In order to test the Markov switching model against the null hypothesis of no switching model, the null model of random walk with a drift is estimated and the estimated log-likelihood function is -7710.41. This test is complicated by the fact that certain parameters of the Markov switching model are unidentified in the null model as discussed in Bonomo and Garcia (1993). Garcia (1992) derives a non-standard asymptotic distribution of the log-likelihood ratio test of the random walk null hypothesis and the general two-stage Markov switching model, in which the critical values at the 1-percent and 5-percent levels are 17.38 and 14.11, respectively. Since the log-likelihood value of the two Markov switching models is -6307.4294, the null of no switching is strongly rejected in favour of these two models at these critical values.

The Markov switching models in Table 3 are tested against their simple switching counterpart in Table 2 in order to test the restrictions that lead to the probabilities of state being independent from the state during the previous period.

This testing of the hypothesis faces the same complication as does the test comparing the Markov switching model to the null model of no switching, and as a result the likelihood ratio statistics will have a non-standard distribution. However, the likelihood ratio statistics of both the "Switching in Mean and Variance" pair and the "Switching in Variance" pair, as reported in the last row of Table 3, are very large, such that the simple switching models are likely to be strongly rejected.

The results in Table 3 present interesting characteristics of switching regimes. The estimated coefficients in the first column show two regimes one with a mean of 0.1058 and relatively low variance. The mean and standard deviation of the returns over the sample are 0.1077 and 1.4191, respectively. Thus, this regime describes days with average returns and relatively low variance. The mean of the second regime is slightly higher, but does not differ statistically from the one just described. However, the difference in variance is very noticeable. The variance in this regime is about four times greater than that in the alternate regime; therefore, this regime will be called a high variance regime, while the other will be called a low variance regime. The transitional probabilities show that, once the stock market has settled into it, the low variance regime is very persistent. The probability that this regime will continue from one period to the next is .975, which implies that its influence over the stock market can be expected to continue for approximately 40 days.¹⁰ The high variance regime is less persistent, with a probability of continuation of .9213, or an expected duration of 13 days.

¹⁰ The expected duration is calculated as $(1-p_{ii})^{-1}$, see Hamilton (1989), 374.

IV A. Contemporaneous and Lag Volume

The first multivariate specification similar to equation (2) examines the interaction of contemporaneous volume and returns under a two-state Markov switching model. The measure of volume used is the growth rate between the previous day's trading volume and that of the current day, which will be referred to simply as volume. For example, "high volume" would mean an instance where the daily growth rate is high. In Table 4, it is seen that contemporaneous volume is positively related to returns in both regimes. In the low-variance regime, the average mean is 0.1082 and the coefficient of volume is 0.0999. Since the volume series has been transformed to have a zero mean and unit variance, this means that an increase in volume of one standard deviation from the mean can almost double the returns, and a decrease in volume of one standard deviation from the normal average will almost wipe out the positive average returns on a particular day of stock market trading if this regime is in effect.

The influence of volume is more pronounced in the high-variance regime. Conditional returns under this regime are completely dominated by the variation in volume. The average return under this regime is 0.0894. However, a shift of volume of one standard deviation in a positive direction will increase the returns ten-fold, to 0.8546. This indicates that volume plays a very important role in pricing stock, which supports the need to understand what trading volume represents.

Earlier theoretical models, such as Copeland (1976), associate volume with the arrival of information about stocks on the market. LeBaron (1993) presents an alternative line of thought, namely, that trade in financial markets may be self-generated, and the positive feedback between stock returns and volume can be a result of a trading process unrelated to variations in the stock fundamental.

Another advantage of studying returns in conjunction with volume can be seen in the log-likelihood values. Unlike in the univariate specification, the values related to the two specifications differ from each other and indicate that switching in mean and variance is a better specification when return and volume are modelled together. In the following estimation, both specifications are reported in order to verify whether this superiority holds throughout, but the discussion will focus only on the estimated coefficients of the two means-two variances specification, except when a comparison is enlightening.

The models in Table 5 further enrich the specification by allowing volume to influence not only the mean of the distribution, but also the transitional probabilities between stock market states, as in equation (3). This is a time-varying transitional probabilities specification, since the probability of moving from one state to another on any given trading day throughout the sample period varies in accordance with the influence of volume on that day. Interestingly, volume has opposite effects on the persistence of each regime. For the low-variance regime, the effect of volume on the probability that the regime will continue from one day to the next is negative and statistically significant. Thus, the chance that the stock market will switch from a

low-variance state to a high-variance state is greater if the current volume is high, whereas the chance that it will remain in a low-variance regime increases with low volume. The effect of this influence may not be dramatic, as the influence exerted by volume is small in comparison with the average persistence probability.

Volume has a different effect on the high-variance regime. Here, the influence of volume has a positive coefficient. High volume on the current trading day increases the probability that the high-variance regime will continue from the previous day. Volume may play an important role in perpetuating this regime. Its influence is about one-third the size of the average persistence probability of this regime. An increase in volume of one standard deviation extends the expected duration of this regime from 14 days to 38 days.¹¹ All estimates in this table are statistically significant except for μ_1 , the average mean of the high-variance regime.

The emerging picture of how volume affects return and influences the transitional probabilities between states of the stock market is even more intriguing in light of the practice of technical analysis. Technical analysts usually rely on mechanical trading rules to signal price trends, and it is known that they pay a great deal of attention to volume in order to identify stock price trends. For example, one technical trading rule that uses volume information is the Cumulative Volume, Relative Strength, Moving Average (CRISMA) trading system proposed by Pruitt and White (1988); its out-of-sample performance is evaluated in Pruitt, Tse, and White

¹¹ These two values correspond to $[1 - \Phi(1.4727)]^{-1}$ and $[1 - \Phi(1.4727+0.4652)]^{-1}$, respectively.

(1992).¹² However, the estimation in this paper reveals that the informational content of volume is not a static, easy-to-grasp concept. The extent of its effect on daily stock returns depends on which regime governs the stock market on any given day.

The next estimation replaces contemporaneous volume with one-day lag volume. If the effect of volume on returns is persistent, volume might have a predictive power for future returns.

Table 6 should be compared to the results in Table 4. The variance estimates and the transitional probabilities are similar to those in Table 4, but the effect of volume on mean returns is different. Although the lag volume has a positive effect on current period returns in both regimes, this effect is not as strong as that of contemporaneous volume. It was found earlier that an increase in current volume can result in a ten-fold increase in current returns in the high-variance regime; however, in this same regime an increase in lag volume of one standard deviation over its normal level will only double the normal current returns. In addition, both the average mean and the influence of lag volume in the high-variance regime are not statistically significant in this specification.

Lag volume does have some predictive power in the low-variance regime. Under this regime, a change in volume of one standard deviation will result in an increase or decrease of only one-third of the regular returns. This effect on the mean is maintained when the estimation is constrained to have a single mean and a switch in variance only, as seen in column 2. Whether the predictive power of volume within a

¹² For a more general reference of the important role volume plays in technical analysis, Lebaron (1992) refers to Colby and Meyers (1988).

Markov switching structure will be meaningful in generating excess returns when used in trading strategies is another interesting subject that has not been explored.

The effect of lag volume on transitional probabilities is reported in Table 7. The estimation will show whether the previous day's volume has any effect on the likelihood that a given regime will persist from one day to the next. Unlike in Table 5, the effect of lag volume on the persistence probability is now negative for both regimes. Neither estimate is statistically significant no matter which specification is used, be it Switching in Mean and Variance or Switching in Variance only. As far as the mean return is concerned, in the two means-two variances model lag volume has no statistically significant effect on mean in either regime. If the estimation is constrained to Switching in Variance only, the effect of lag volume on mean is the same as that seen in the previous table (Table 6), or about one third of average returns.

As a side discussion, it is interesting to demonstrate what information these estimates might have revealed had the effects of lag volume on persistence probabilities been statistically robust. For the low-variance regime, high volume on any given day reduces the chance that this regime will persist into the next day. This effect is congruent with that of contemporaneous volume. However, if the high-variance regime is in effect, high volume on a given day also reduces the chance that it will persist into the next day. Viewing these results together with the results obtained from the study of the effect of contemporaneous volume on persistence probabilities, it can be recapitulated that high trading volume today increases the

chance that a high-variance regime will continue from yesterday but decreases the chance that this regime (if operating today) will persist into tomorrow. On the other hands, high trading volume today decreases the chance that a low-variance regime will continue from yesterday and also decreases the chance that this regime (if operating today) will persist into tomorrow.

IV B. Contemporaneous and Lag Relative Volume

Many empirical estimations involving volume show that the results can be sensitive to the manner by which the volume series is transformed into a stationary series.

Campbell, Grossman, and Wang (1993), in their investigation of volume as an explanation for serial correlation in stock returns, obtained much weaker results when using a model of volume based on deviation from an unobserved component than when using a model based on the deviation from the moving average trend. Lebaron (1992) found opposite results using a measure of volume in relation to its long-term average vis-a-vis a measure in relation to its short-term average. He also found the log difference of volume to be too noisy to be useful in the estimation. The results in section IV A show that the Markov switching specification can capture the effect of volume even in a fast-moving measure. It is interesting to see how robust the results in section IV A are in comparison with an alternative measure of volume.

Since both studies cited in the previous paragraph prefer to use a measure of volume relative to a slow-moving trend, such as a 100- to 200-day moving average of

its past value, this section will use the same transformation. The daily volume series is transformed as:

$$tv_t = \log \left(\frac{v_t}{mv100_t} \right)$$

$$\text{where } mv100_t = \frac{1}{n} \left(\sum_{i=0}^{n-1} v_{t-i} \right), \quad n=100$$

This transformed volume series will be called "relative volume" for purposes of emphasis, but otherwise will continue to be called simply "volume" for the sake of convenience. The series is plotted in Figure 5. The pattern of this series looks less noisy in comparison with Figure 3, which is the volume series used previously. The mean and standard deviation of this series are -0.0442 and 0.3046. The estimations in Tables 8–11 repeat those of Tables 4–7 using relative volume instead of the log difference volume series. The results will be discussed briefly, focusing on where the results differ from those of the previous estimation.

In Table 8, the overall results from using relative volume are similar to those obtained from using volume. There are two regimes, one with a higher variance. The low-variance regime is highly persistent. The effect of contemporaneous relative volume is strong, especially in the high-variance regime. The average mean of the high-variance regime is now slightly negative; however, because of the estimate's large standard deviation, it is still difficult to distinguish from the average mean in the low-variance regime.

In Table 9, the effects of volume on persistence probabilities continue to have opposite signs, namely, negative in the low-variance regime and positive in the high-variance regime, but the statistical significance has changed. In the two means-two variances regime, the effect of volume on the persistence probability of the high-variance regime has now lost its significance. In the Switching in Variance only specification, the effect of volume on persistence probabilities is insignificant for both regimes. These results show that the Markov switching specification, in the previous estimations, discovers effects of volume that cannot be strongly detected by a measure of volume relative to a slow-moving trend. It is common to find that volume results are sensitive to the measure of volume used, but the sensitivity found here is the reverse of that found in the usual experiences. While many authors find that using a fast-changing measure of volume gives inferior, if not entirely uninformative, results, it is found here that interesting relationships can be seen with the use of the Markov switching specification, even when the transformation of volume is measured on the same time scale as are returns.

The predictive power of lag relative volume on current period returns is examined in Table 10. The improvement over Table 6 is that the predictive power of lag volume in a high-variance regime is statistically significant. Thus, transforming volume in this way makes the influence of lag volume on returns statistically significant in both regimes. However, as before, the average returns in a high-variance regime are not significant. The Switching in Variance specification shows that the predictive power of lag volume, in comparison with Table 6, marginally increases in

magnitude. When relative volume is at its mean, the expected mean return is 0.1153.¹³ An increase in relative volume of one standard deviation above its mean will add 0.0598 to the expected mean returns.¹⁴ Thus the influence of relative volume is about half the magnitude of the expected mean returns, while using volume series, as in Table 6, the influence is about one-third the expected mean returns.

The last estimation, in Table 11, examines the influence of lag relative volume on transitional probabilities. Similar to Table 7, the influence of lag relative volume to persistence probabilities is negative in both regimes. The improvement over Table 7 is that this effect is now significant in the low-variance regime, although the effect in the high-variance regime remains insignificant. Thus, in this estimate, it can be stated that conditional on relative volume, high relative volume yesterday decreases the probability that a low-variance regime will continue from yesterday. In addition, the lag relative volume now has a statistically significant effect on returns in both regimes (similar coefficients are not significant in Table 7). It seems that, for this specification, stronger statistical results are obtained by using relative volume, which is similar to the experience of other researchers. Of all the specifications estimated, this specification will be a better choice for testing the usefulness of volume in forecasting next-period returns or in formulating simple trading rules.

¹³ This is calculated from $0.1240 + [0.1963 \times (-0.0442)]$. The second term is the product of the estimated effect of relative volume and its sample mean.

¹⁴ This is a product of the coefficient of this effect, which is 0.1963, and the sample standard deviation of the relative volume series, which is 0.3046.

When the Switching in Mean and Variance model is tested against the Switching in Variance model, the log-likelihood test statistic is 6.1884. This test statistic has a chi-square distribution with two degrees of freedom. The Switching in Variance only model is rejected against the alternative of Switching in both Mean and Variance, with a significance level of 0.04531.

V. Conclusion

Using the Markov switching model to explore the relationship between daily returns and trading volume on the stock market in Thailand has revealed many interesting relationships between these two series. Firstly, stock returns in Thailand fit the two-state Markov switching process, in which one regime has a substantially higher variance than the other. Secondly, contemporaneous volume is positively related to returns, but its influence is much stronger when the stock market is in a high-variance state. This effect operates independently from the effect of volume on the transitional probabilities of stock market states. In addition, an increase in lag relative volume of one standard deviation can increase expected returns by up to one half. Fourthly, contemporaneous volume has a negative effect on the persistence probability of the low-variance regime and a positive effect on that of the high-variance regime. These effects are more statistically significant when using volume than when using relative volume. Lag volume has a negative effect on the persistence probabilities of both regimes, but these effects are statistically weak; a statistically stronger significance is obtained when using lag relative volume. The fifth finding relates to a regular

problem that faces estimations involving volume. It is commonly found that the results are sensitive to the choice of volume measure, such as the daily growth rate vis-a-vis a measure of volume relative to its local average. In some cases in the previous literature, fast-changing measures of volume turned out to be uninformative. On the contrary, the model used in this paper produces rather robust findings with the use of this choice of transformation of volume series. Interesting relationships are found using the daily growth rate of volume, and the results have a higher statistical power than those obtained using an alternative measure in some specifications.

An obvious extension of research is the question of whether these results can be replicated using data from a mature stock market, such as the New York Stock Market. At the current stage of empirical research on the relationship between daily returns and volume, no general stylized fact has yet been established, thus it is still difficult to know whether these results relate to any special characteristics of the Thai stock market or are common to any market. Moreover, this model has not yet been applied to data from any other market. Perhaps an extension of the specification to enrich variance structures in each regime will yield further interesting dynamics.

In this paper, volume affects the choice of low- and high-variance states. One choice of modelling is to allow volume to have a finer effect on variances, similar to how it affects mean returns in each regime. Another product that can be calculated from the Markov switching estimation is that of smoothed probabilities. The estimated transitional probabilities in this paper are the ex ante probabilities that a regime will switch or persist at time t , conditional on the information up to time t ,

calculated in such a way as to obtain optimal estimates of the parameters in the model. With all these estimated parameters, it is possible to calculate smoothed probabilities, namely, ex post probabilities that returns at time t come from regime i , conditional on the information that all the returns in other time periods are in their specific regimes. The plot of these smoothed probabilities can be considered in light of actual events on the stock market and can be instructive about the economic interpretation of the switching process.

A further issue for research is directly suggested by the predictive power of lag volume on returns and on the persistence probabilities of stock market states. Since there is evidence that professional investors believe volume to contain valuable information about price trends, a trading rule can be formulated based on the estimated Markov switching model of returns and lag volume. The rule can be tested to see whether the relationship discovered here can generate sizable excess returns. Engle (1994) finds that the univariate Markov model is good at predicting the direction of change of the exchange rate. It will be interesting to pursue the possibility of using the Markov structure together with trading volume to predict stock returns.

A more important task is to link the estimated empirical relationship with the theoretical model that relates volume to stock returns. It is not obvious which of the current models can be related appropriately to the Markov switching structure at high frequency. Alternatively, the return process may be a switching process between different models of volume and returns, such as one driven by noninformative trading in one regime and by the sweeping force of fad or herd behaviour in another regime.

Table 1: Summary Statistics of Return and volume

	DVRMWD	TRDVOL	V	TV
Mean	0.1077	11189.82	0.0000	-0.0442
Std.Dev.	1.4191	33643.19	1.0000	0.3046
Minimum	-9.6656	1.00	-7.6037	-2.4915
Maximum	15.1229	425473.00	7.3632	1.0263
Skewness	0.1181	6.01	-0.1208	-0.1636
Kurtosis	13.8025	47.74	4.7528	1.0374

- Note: 1. Total number of observations is 4,359 for each series.
 2. DVRMWD is the daily value weighted return with cash dividend, expressed in percent.
 3. TRDVOL is daily trading volume, in 1,000 units.
 4. V is the normalised log first difference of TRDVOL.
 5. TV is the log of the ratio between TRDVOL and its previous 100-day moving average.

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Table 2: Simple Switching Model of Returns

	Normal Mixture	Volatility Regimes
μ_0	0.1070 (0.0145)	0.1072 (0.0139)
μ_1	0.1109 (0.1161)	
γ_{p0}	-0.9461 (0.0543)	-0.9463 (0.0540)
α_0	0.7382 (0.0181)	0.7383 (0.0180)
α_1	3.0133 (0.1169)	3.0136 (0.1166)
Log-likelihood	-6716.3908	-6716.4344

Note: The probability of state can be calculated from the estimated coefficient as $p0 = \Phi(\gamma_{p0})$.

Table 3: Markov Switching Model of Returns

	Switching in Mean and Variance	Switching in Variance
μ_0	0.1058 (0.0137)	0.1061 (0.0130)
μ_1	0.1138 (0.0801)	
γ_{p0}	1.9606 (0.0627)	1.9610 (0.0625)
γ_{q0}	1.4138 (0.0778)	1.4138 (0.0778)
α_0	0.6876 (0.0137)	0.6877 (0.0135)
α_1	2.6233 (0.0743)	2.6240 (0.0738)
Log-likelihood	-6307.4294	-6307.4294
LR	817.9228	818.0100

Note: 1.The transitional probabilities can be calculated from the estimated coefficients as $p_{00} = \Phi(\gamma_{p0})$ and $p_{11} = \Phi(\gamma_{q0})$.
 2.The row LR reports the likelihood ratio statistics for the test of each model in this table against its simple switching counterpart in Table 2.

Table 4: Markov Model of Returns and Influence of Contemporaneous Trading Volume on Returns

	Switching in Mean and Variance	Switching in Variance
μ_0	0.1082 (0.0134)	0.1120 (0.0130)
β_0	0.0999 (0.0118)	0.1061 (0.0118)
μ_1	0.0894 (0.1166)	
β_1	0.7652 (0.1127)	
γ_{p0}	1.9682 (0.0624)	1.9803 (0.0623)
γ_{q0}	1.4180 (0.0781)	1.4063 (0.0784)
α_0	0.6810 (0.0130)	0.6892 (0.0126)
α_1	2.5672 (0.0719)	2.6698 (0.0740)
Log-likelihood	-6243.0034	-6266.4548

Note: The transitional probabilities can be calculated from the estimated coefficients as $p(0) = \Phi(\gamma_{p0})$ and $p(1) = \Phi(\gamma_{q0})$.

Table 5: Markov Model of Returns and Influence of Contemporaneous Trading Volume on Transitional Probabilities

	Switching in Mean and Variance	Switching in variance
μ_0	0.1030 (0.0136)	0.1083 (0.0130)
β_0	0.0972 (0.0116)	0.1037 (0.0118)
μ_1	0.0864 (0.0928)	
β_1	0.7639 (0.1098)	
γ_{p0}	1.9470 (0.0660)	1.9630 (0.0656)
γ_{pv}	-0.1695 (0.0569)	-0.1797 (0.0551)
γ_{q0}	1.4727 (0.0876)	1.4513 (0.0860)
γ_{qv}	0.4652 (0.1115)	0.4509 (0.1051)
α_0	0.6696 (0.0137)	0.6798 (0.0132)
α_1	2.5339 (0.0718)	2.6447 (0.0743)
Log-likelihood	-6231.4520	-6256.1240

Note: The transitional probabilities can be calculated from the estimated coefficients as $p_{00} = \Phi(\gamma_{p0} + \gamma_{pv} V_t)$ and $p_{11} = \Phi(\gamma_{q0} + \gamma_{qv} V_t)$.

Table 6: Markov Model of Returns and the Influence of Lag Trading Volume on Returns

	Switching in Mean and Variance	Switching in Variance
p_0	0.1070 (0.0138)	0.1075 (0.0131)
β_0	0.0334 (0.0129)	0.0339 (0.0106)
μ_1	0.1081 (0.2277)	
β_1	0.1182 (0.2799)	
γ_{p0}	1.9665 (0.0630)	1.9687 (0.0626)
γ_{q0}	1.4206 (0.0789)	1.4213 (0.0781)
α_0	0.6880 (0.0136)	0.6888 (0.0134)
α_1	2.6253 (0.0745)	2.6294 (0.0737)
Log-likelihood	-6301.0579	-6301.6244

Note: The transitional probabilities can be calculated from the estimated coefficients as $p_{00} = \Phi(\gamma_{p0})$ and $p_{11} = \Phi(\gamma_{q0})$.

Table 7: Markov Model of Returns and Influence of Lag Trading Volume on Transitional Probabilities

	Switching in Mean and Variance	Switching in Variance
μ_0	0.1057 (0.0160)	0.1064 (0.0148)
β_0	0.0324 (0.0230)	0.0339 (0.0135)
μ_1	0.1129 (0.3288)	
β_1	0.1184 (0.5210)	
γ_{p0}	1.9619 (0.2219)	1.9641 (0.2313)
γ_{pv}	-0.0346 (0.1337)	-0.0340 (0.1485)
γ_{q0}	1.4381 (0.3691)	1.4387 (0.2995)
γ_{qv}	-0.1960 (0.8528)	-0.1956 (0.4195)
α_0	0.6860 (0.0206)	0.6869 (0.0206)
α_1	2.6209 (0.2845)	2.6253 (0.2864)
Log-likelihood	-6300.4042	-6301.0143

Note: The transitional probabilities can be calculated from the estimated coefficients as $p(0) = \Phi(\gamma_{p0} + \gamma_{pv} V_{t-1})$ and $p(1) = \Phi(\gamma_{q0} + \gamma_{qv} V_{t-1})$.

Table 8: Markov Model of Returns and Influence of Contemporaneous Relative Trading Volume on Returns

	Switching in Mean and Variance	Switching in Variance
μ_0	0.1571 (0.0154)	0.1558 (0.0146)
β_0	0.4982 (0.1030)	0.5132 (0.1087)
μ_1	-0.0325 (0.1977)	
β_1	1.9722 (0.3220)	
γ_{p0}	1.9697 (0.2238)	1.9767 (0.2097)
γ_{q0}	1.4016 (0.3363)	1.3940 (0.2996)
α_0	0.6791 (0.0187)	0.6841 (0.0162)
α_1	2.5990 (0.2845)	2.6821 (0.2304)
Log-likelihood	-6209.7878	-6231.8008

Note: The transitional probabilities can be calculated from the estimated coefficients as $p_{00} = \Phi(\gamma_{p0})$ and $p_{11} = \Phi(\gamma_{q0})$.

Table 9: Markov Model of Returns and Influence of Contemporaneous Relative Trading Volume on Transitional Probabilities

	Switching in Mean and Variance	Switching in Variance
μ_0	0.1593 (0.0143)	0.1578 (0.0151)
β_0	0.4996 (0.0420)	0.5154 (0.1051)
μ_1	-0.0493 (0.0727)	
β_1	2.0045 (0.3378)	
γ_{p0}	1.9484 (0.0674)	1.9635 (0.3012)
γ_{pv}	-0.9185 (0.2202)	-0.9376 (2.8828)
γ_{q0}	1.3566 (0.0806)	1.3543 (0.3459)
γ_{qv}	0.2246 (0.6352)	0.1325 (1.7959)
α_0	0.6765 (0.0130)	0.6826 (0.0207)
α_1	2.6005 (0.0733)	2.6891 (0.3164)
Log-likelihood	-6197.7570	-6220.1622

Note: The transitional probabilities can be calculated from the estimated coefficients as $p(0) = \Phi(\gamma_{p0} + \gamma_{pv} TV_t)$ and $p(1) = \Phi(\gamma_{q0} + \gamma_{qv} TV_t)$.

Table 10: Markov Model of Returns and Influence of Lag Relative Trading Volume on Returns

	Switching in Mean and Variance	Switching in Variance
μ_0	0.1249 (0.0144)	0.1240 (0.0136)
β_0	0.1904 (0.0430)	0.1963 (0.0420)
μ_1	0.0637 (0.0814)	
β_1	0.7210 (0.2902)	
γ_{p0}	1.9657 (0.0629)	1.9638 (0.0631)
γ_{q1}	1.4152 (0.0785)	1.4138 (0.0788)
α_0	0.6878 (0.0136)	0.6874 (0.0136)
α_1	2.6252 (0.0742)	2.6320 (0.0744)
Log-likelihood	-6292.0804	-6295.1310

Note: The transitional probabilities can be calculated from the estimated coefficients as $p_{00} = \Phi(\gamma_{p0})$ and $p_{11} = \Phi(\gamma_{q0})$.

Table 11: Markov Model of Returns and Influence of Lag Relative Trading Volume on Transitional Probabilities

	Switching in Mean and Variance	Switching in Variance
μ_0	0.1275 (0.0143)	0.1263 (0.0136)
β_0	0.1929 (0.0430)	0.1986 (0.0422)
μ_1	0.0540 (0.1485)	
β_1	0.7344 (0.3336)	
γ_{p0}	1.9471 (0.0645)	1.9454 (0.0649)
γ_{pv}	-0.5930 (0.2238)	-0.5922 (0.2115)
γ_{q0}	1.4061 (0.0793)	1.4065 (0.0794)
γ_{qv}	-0.1137 (0.1069)	-0.1405 (0.1399)
α_0	0.6893 (0.0136)	0.6888 (0.0136)
α_1	2.6358 (0.0742)	2.6424 (0.0749)
Log-likelihood	-6287.9839	-6291.0781

Note: The transitional probabilities can be calculated from the estimated coefficients as $p(0) = \Phi(\gamma_{p0} + \gamma_{pv} TV_{t-1})$ and $p(1) = \Phi(\gamma_{q0} + \gamma_{qv} TV_{t-1})$.

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