Profits on Technical Trading Rules and Time-Varying Expected Returns:

Evidence from Pacific-Basin Equity Markets

by

Akitoshi Ito
Richard Ivey School of Business

Submitted in partial fulfilment
of the requirements for the degree of
Doctor of Philosophy

Faculty of Graduate Studies
The University of Western Ontario
London, Ontario
September 1997

0-612-32313-7

Abstract

The purpose of this thesis is to evaluate the profitability of technical trading rules in Pacific-basin equity markets in the context of asset pricing models. Specifically, this thesis examines whether technical rule profits are consistent with time-varying expected returns implied by equilibrium asset pricing models in an international context.

Another goal of this thesis is to investigate the issue of market integration and segmentation by focusing on the relationship between the technical rule returns and international market structure. This thesis examines three different types of market structure; complete integration, "mild segmentation" (Errunza and Losq 1985), and complete segmentation.

The same set of technical rules as Brock et al. (1992) are applied to the Japanese, the U.S., Canadian, Indonesian, Mexican, and Taiwanese equity indices. The results from the standard tests indicate that the technical rules have significant forecast power for all the countries, except for the U.S. However, the results from the bootstrap tests indicate that the profits for Japan, the recent sample of Canada, and Taiwan are consistent with some equilibrium asset pricing models (mainly, the asset pricing model under mild segmentation) when a conventional significance level is used. None of the equilibrium models are consistent with the trading profits for Indonesia, Mexico, and the early 1980's of Canada. The overall results indicate that taking into account time-varying expected returns is important to evaluate the profits of the trading rules. In addition, it is demonstrated that the bootstrap simulations using the technical rules can provide additional information on the market structure characterizing the equity markets which this thesis examines.

Keywords: technical analysis, trading rule, Pacific-basin markets, time-varying expected return, mild segmentation, GARCH-M model

Acknowledgements

Throughout this thesis, I was helped and encouraged by many people. In particular, I would like to thank my supervisors, Steve Foerster and Andrew Karolyi, for their continual support and interest in this research. Without their help and guidance, this study would not have been completed. Their intellectual energy and insight not only stimulated my enthusiasm for this thesis but also have greatly enlightened me far beyond this thesis.

I would also like to thank Joe Kairys for his support during my course work at the University of Western Ontario. In particular, he opened my interest in technical analysis. I have benefitted from discussions with John Schmitz, a fellow doctoral student at the Ivey School of Business, University of Western Ontario. And, special thanks to Shige Makino of the Chinese University of Hong Kong for his support in the early stage of my doctoral studies. I am also indebted to fellow doctoral students for their comments and suggestions at various seminars at the Ivey School of Business.

I would like to thank Professor Tsuneo Yahagi of Keio Business School for his guidance and encouragement while I was an MBA student at Keio. Pursing an academic career was a difficult task for me, and I was able to choose this career for his thoughtful guidance and encouragement.

Special thanks go to Okada and Mizuno family in Nagoya for their support such as sending us various information on Japan. I am grateful to my parents, brother, and sister for their always present support and encouragement. Leaving them in Japan was a sort of concern to me, but I can go home now.

Finally, my wife, Yasuko, helped me in various ways, easing my mind, encouraging my idea, and sometimes acting as a critical examiner to aim to improve my thesis. I would like to thank her for all her support and encouragement.

Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

The purpose of this thesis is to evaluate the profitability of technical trading rules in Pacific-basin equity markets in the context of asset pricing models. Specifically, this thesis examines whether the technical rule profits are consistent with the time-varying expected returns implied by equilibrium asset pricing models.

Another goal of this thesis is to investigate the issue of market integration and segmentation by focusing on the relationship between the technical rule returns and international market structure. This thesis examines three different types of market structure with varying degrees of segmentation; complete integration, "mild segmentation" (Errunza and Losq 1985), and complete segmentation.

Technical analysis attempts to detect a "hidden" trend in the movements of security prices by looking at the patterns of the past prices. Technical analysis has been popular among practitioners for several decades. Among scholars, most early empirical studies on technical analysis find that technical analysis does not lead to profitable strategies. These studies include Alexander (1961, 1964) and Fama and Blume (1966). In contrast, recent studies provide evidence that some simple technical trading rules have considerable forecast power and are profitable. Brock, Lakonishok, and LeBaron (1992) find that some technical trading rules can predict future returns on the Dow Jones Industrial Average over the 90-year period. Their results from the tests based on the bootstrap methodologies indicate that none of the popular statistical models they examine (the random walk, the first-order autoregressive model, and two models incorporating the conditional heteroscedasticity) are consistent with the trading rule profits. Bessembinder and Chan (1995) extend the study of Brock et al. (1992) to Asian equity markets and find the significant forecast power of the trading rules for these markets.

There are at least two interpretations for the finding that the technical trading rules can predict future returns on securities. The first interpretation is that capital markets are inefficient. The second interpretation is that markets are efficient and that the forecast power of the technical trading rules reflects the time-variation of expected returns which is driven by the shift of equilibrium due to new information. In fact, many studies have presented evidence that expected returns on stocks and other assets vary over time (Keim and Stambaugh 1986; Fama and French 1989; Harvey 1991; Cambell and Hamao 1992; Ferson and Harvey 1993; Ferson, Foerster and Keim 1993).

Despite the accumulated empirical evidence for time-varying expected returns, none of the studies examining technical trading rules for stock markets have directly tested a conjecture that the technical trading rules capture the time-varying expected returns on stocks implied by equilibrium asset pricing models. Brock et al. (1992) examine purely statistical and univariate-type models and do not impose on the models any cross-sectional restrictions that are generally implied by asset pricing models. Bessembinder anc Chan (1995) provide indirect evidence (a substantial cross-market correlation in trading signals) for the hypothesis that the technical trading rules capture the time-varying expected returns determined in the global capital market. However, they do not test the trading rules against any specific asset pricing models. Thus, an important contribution of this thesis is to evaluate the profitability of technical trading rules for equity markets by using as a benchmark model the equilibrium asset pricing models which allow for the time variation of expected returns. For currency futures markets, Kho (1996) applies the bootstrap methodologies used by Brock et al. (1992) to some versions of the conditional international capital asset pricing model. Following Kho (1996) and Brock et al. (1992), this thesis utilizes the bootstrap methodologies in assessing the trading rule profits. Specifically, the empirical distributions of the trading rule returns are computed under an equilibrium model as a null model. The profits obtained from the actual series are compared with the empirical distributions of the trading rule returns.

Whether financial markets are internationally integrated is a controversial issue in the international finance literature (Stulz 1995). This issue is important because the form of pricing relation among assets is substantially different. Recent studies showing that international asset pricing models hold under integration include Harvey (1991), Chan, Karolyi, and Stulz (1992), Ferson and Harvey (1993, 1996), and Dumas and Solnik (1995). On the other hand, studies showing market segmentation include Jorion and Schwartz (1986), Errunza, Losq, and Padmanabhan (1992), and Bekaert and Harvey (1995, 1997). Complete integration and complete segmentation are two extremes of possible international market structure. Alternatively, Errunza and Losq (1985) examine asset pricing relation under a middle-ground type of market structure characterized by an asymmetric access to financial markets between two countries. The market structure which Errunza and Losq (1985) examine is termed by "mild segmentation."

Since there has been no unequivocal agreement about the issue of market integration and segmentation in the past literature, this thesis uses three different types of asset pricing models corresponding to complete integration, mild segmentation, and complete segmentation to evaluate the trading rule profits. To connect technical analysis with the international asset pricing literature forms another important contribution of this thesis. Bessembinder and Chan (1995) has brought an international context to the technical analysis literature; their empirical results indicate the possible existence of country-specific risk premiums correlated to local trading signals, which can be interpreted as an indication of segmentation. However, they do not explicitly take into account the effects of market segmentation on time-varying expected returns in testing the trading rule profits. Thus, the use of asset pricing models corresponding to various types of market structure substantially differentiates this thesis from Bessembinder and Chan (1995).

The conditional mean-variance framework is used to incorporate a set of asset pricing models into a single framework. Specifically, complete integration assumes no investment barriers; under this assumption, the expected returns are determined by the world version of the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965) and extended by Solnik (1974) and Stulz (1981a) in which only the covariance with the world market portfolio is priced. Mild segmentation assumes one-way barriers against capital flow from the foreign market into the domestic market, leading to the asset pricing model in which the covariance with the domestic (regulated) market, as well as the covariance with the world market portfolio, is priced for domestic securities (Errunza and Losq 1985). Finally, complete segmentation assumes two-way barriers, leading to the purely domestic CAPM in which only the covariance with the domestic market is priced for domestic securities.

The technical trading rules to be examined in this thesis are the same set of rules as Brock et al. (1992) examine, i.e., two different types of moving average rules and trading range break rules. The countries to which the technical trading rules are applied include Japan, U.S., and Canada among developed markets, and Indonesia, Mexico, and Taiwan among emerging markets. Daily data on equity market indices for theses countries are obtained from Datastream International. The sample period for the developed markets is 1980-1996. For the emerging markets, data during the period mainly from 1988 to 1996 are used. Trading rule returns are computed for each index, and standard test statistics are applied to the returns. The results indicate that the trading rules exhibit statistically significant forecast power for all countries, except for the U.S. The cross-sectional pattern of the results indicates that the technical trading rules have stronger forecast power for the emerging markets than for the developed markets. For the buy-sell spread, the average values across all trading rules and three emerging markets is 0.2302% per day or 77.8%on an annual basis; the averages across all trading rules and developed markets with significant forecast power of the trading rules (i.e., the Japan and Canada indices) is 0.1030% per day or 29.4% on an annual basis. A simple adjustment for the spurious autocorrelations due to nonsynchronous trading does not completely explain significant forecast power of the trading rules. The profitability of a specific trading strategy with transaction costs is also examined.

The conditional asset pricing models corresponding to three different types of market structure are estimated by following an approach taken by Chan, Karolyi, and Stulz (1992), who relate the expected returns to the conditional second moments that are to be estimated jointly with the expected returns, under a bivariate setting of the domestic versus foreign markets. In the models, the second moments of returns are specified to vary over time by using a bivariate generalized autoregressive conditional heteroscedasticity model (GARCH) of Engle and Kroner (1995). The models are estimated separately for each country. Using the bootstrap methodologies, the empirical distributions of trading rule returns are constructed, and the actual returns are compared with them. The results are summarized as follows: the trading rule profits for Japan, the second half period of Canada, and Taiwan are consistent with some asset pricing models (mainly the asset pricing model under mild segmentation) at the 5 percent significance level; none of the equilibrium models are consistent with the actual profits for Indonesia, Mexico, and the first half period of Canada; all three models are consistent with the actual trading rule returns for the U.S. market.

It is demonstrated that taking into account the time-varying expected returns implied by equilibrium asset pricing models is important to evaluate the profitability of the technical trading rules. Although the standard tests which compare the trading rule returns with the unconditional mean return on the buy and hold find that the trading rules yield significant profits for five countries (with the only exception of the U.S.), the bootstrap tests indicate that for Japan, the recent sample of Canada, and Taiwan out of the five countries, the actual trading rule profits are consistent with some equilibrium models at the conventional significance level of 5 percent. In addition, it is demonstrated that the results from the bootstrap simulations using the technical trading rules can provide additional information on the market structure characterizing the equity markets which this thesis examines. The actual trading rule returns are consistent with the mild segmentation of Japan, the recent sample of Canada, and Taiwan at the 5 percent significance level.

This thesis is organized as follows. Chapter 2 reviews the relevant previous literature. Chapter 3 explains the technical trading rules to be examined, the methodologies of standard tests, and how the effects of transaction costs on the profitability of the rules are examined.

Chapter 4 discusses the conditional asset pricing models corresponding to three different types of market structure. Chapter 5 explains the testing procedure using the bootstrap methodologies. Chapter 6 describes the data. Chapter 7 presents the empirical results. Chapter 8 concludes this thesis.

Chapter 2 Review of the Relevant Literature

2.1 Empirical studies on technical analysis

Technical analysis attempts to predict future returns on securities by looking at the patterns of past prices. Historically, technical analysis has been used widely among practitioners.

Among scholars, most early empirical studies on technical analysis report evidence that the use of technical analysis is not a profitable strategy. Alexander (1961) tests a number of filter rules,[1] using daily data on the Dow Jones and S&P's stock price indices. He finds that the rules which he examines are profitable relative to the buy-and-hold strategy before transaction costs. However, Alexander (1964) re-examines his results and concludes that the filter rules are not profitable if transaction costs are taken into account. Fama and Blume (1966) compare the profitability of various filter rules to the buy-and-hold strategy, using daily data on the individual stocks of the Dow Jones Index. They find that after adjusting for transaction costs, the filter rules are not profitable. Reviewing the results of both Alexander (1961, 1964) and Fama and Blume (1966), Fama (1970, 1976) subsequently concludes that capital markets are weak-form efficient in the sense that all information on past prices is already reflected in market prices.

Despite the early empirical results, recent studies have shown that some simple technical trading rules can predict future returns and are profitable. Such recent studies include those examining currency markets and equity markets. Sweeney (1986) applies the filter rule techniques to daily foreign exchange rates and finds that the techniques yield statistically significant profits. Sweeney (1988) replicates the study of Fama and Blume (1966), using the

---

[1] Filter rules are one of the popular technical trading rules. The rules emit buy signals if the price rises by a prespecified percentage and sell signals if the price declines by the same percentage.

recent sample of the individual stocks in the Dow Jones index. He finds that the filter rules make a profit exploitable to floor traders after controlling transaction costs. Levich and Thomas (1993) examine several technical trading rules, using data on the daily prices of currency futures and find significantly large profits.

Brock, Lakonishok and LeBaron (1992) (henceforth BLL) have reported evidence that the simplest and most popular technical trading rules have predictive power for the future price changes of daily Dow Jones Index over the period 1897-1986. The trading rules that they examine include moving average rules (buy when the short-term moving average of prices exceeds the long-term moving average and sell when the short-term moving average is less than the long-term moving average) and trading range break rules (buy when the price level moves above a local maximum and sell when it moves below a local minimum). Using standard test statistics, BLL show that the conditional mean buy returns are significantly higher than the conditional mean sell returns before transaction costs over the overall period and over non-overlapping subperiods.

BLL also examine the issue of whether popular and plausible statistical models of equilibrium returns can explain away the observed spread between the mean buy and sell returns. In order to address this issue, BLL employ the bootstrap methodologies inspired by Efron (1979, 1982) and extended by Freedman and Peters (1984). The statistical models which BLL test include the random walk with a drift, the first-order autoregressive model (AR(1)), the generalized autoregressive conditional heteroscedasticity in-mean (GARCH-M) by Engle (1982) and Bollerslev (1986) and the Exponential GARCH (EGARCH) by Nelson (1991). The AR(1) can account for the autocorrelation frequently observed in the index returns (for example, Conrad and Kaul (1989) and Lo and MacKinlay (1990a)). The GARCH-M and EGARCH can account for changing expected returns caused by changes in volatility. The results from the bootstrap simulations indicate that none of the models can explain the spread between the mean buy and sell returns.

Bessembinder and Chan (1995) test the same trading rules as BLL, using data on the daily equity market indices of six Asian countries (Hong Kong, Japan, Korea, Malaysia, Thailand and Taiwan) over the period 1975-1991. They find that the trading rules have predictive power for future price changes in the six markets with the strongest forecastability for the emerging markets of Malaysia, Thailand and Taiwan. Although they use the bootstrap simulations, the null model tested only includes the random walk with a drift.

Bessembinder and Chan (1995) examine three possible conjectures for the predictive power of the trading rules: the positive autocorrelations induced by the nonsynchronous reporting of prices in the index (Scholes and Williams 1977), the mispricings within transaction costs, and the time-varying expected returns under the international asset pricing model. They show that the first and second conjectures can not explain the trading rule results completely. For the third conjecture, they provide evidence for a substantial cross-market correlation in trading rule signals, which is considered to be consistent with the reasoning that the trading rules identify the common variation of equilibrium expected returns determined in the global market. However, they also find that for the emerging markets, local signals are still important after taking into account the common movements in signals, which can be interpreted as an indication of market inefficiencies or country-specific risk premiums.

Kho (1996) examines technical trading rules for currency futures markets and assesses the profits on the rules by using equilibrium asset pricing models for time-varying risk premia and volatility. He applies the moving average rules to data on weekly futures prices over the period 1980-1991 and finds significantly large spread between the conditional mean buy and sell returns. Next, Kho (1996) estimates versions of the conditional international CAPM. Following BLL, Kho (1996) simulates the empirical distributions of trading rule returns with the estimated models and residuals. The results indicate that the simulated distributions are consistent with the actual profits. Thus he concludes that the technical rule profits can be explained by the risk-return relation suggested by the asset pricing theory.

The use of the bootstrap methodologies appears to have become a common approach to the examinations of the technical trading rules. By linking the bootstrap methodologies with technical analysis, BLL develop a technique to test the trading rules under various null models for the process of security returns. Bessembinder and Chan (1995) and Kho (1996) also follow BLL to examine the trading rule profits.

None of the studies examining technical trading rules for stock markets have directly tested a conjecture that the technical trading rules capture the time-varying expected returns on stocks implied by equilibrium asset pricing models. The models BLL examine are purely statistical and univariate-type and they do not impose on their models any cross-sectional restrictions that are generally implied by the asset pricing models. Although Bessembinder and Chan (1995) use the bootstrap simulations, the simulated p-values they report are based on the random walk with a drift, which do not allow for any time variation of expected returns. Thus, an important contribution of this thesis is to evaluate the profitability of technical trading rules for equity markets by using the equilibrium asset pricing models which allow for the time variation of expected returns. For currency futures markets, Kho (1996) applies the bootstrap methodologies used by Brock et al. (1992) to some versions of the conditional asset pricing model. Following Kho (1996) and Brock et al. (1992), this thesis utilizes the bootstrap methodologies in assessing the trading rule profits.

Bessembinder and Chan (1995) have brought an international context to the technical analysis literature. They provide indirect evidence (a substantial cross-market correlation in trading signals) for the technical trading rules capturing the time-varying expected returns determined in the global market. Their results also indicate the importance of local signals and possibly the existence of country-specific risk premiums, which are both related to the issue of market integration and segmentation. However, they do not test the trading rule profits against any specific international asset pricing models nor do they explicitly consider the effects of capital market segmentation on the time-varying expected returns. This thesis makes another important contribution by examining the effects on the trading rule profits of the market integration and different degrees of segmentation. This contribution also substantially differentiates this thesis from Kho's (1996) study.

2.2 Conditional tests of international asset pricing models

Time-varying expected returns are a possible explanation for the technical trading rule profits. Many studies have shown that expected returns vary over time in a way consistent with an asset pricing model in a one-country setting. The evidence for time-varying expected returns has facilitated a conditional test of asset pricing models in an international setting.

Ferson (1995) provides a comprehensive review of studies on theory and empirical tests of conditional asset pricing models which incorporate expected returns and risk that vary over time with economic information. Consumption-based asset pricing models by Breeden (1979) and Lucas (1978) allow expected returns to vary over time and the tests of the consumption-based asset pricing models has incorporated this feature since the early 1980's (Hansen and Singleton (1982, 1984), Dunn and Singleton (1986), Ferson and Constantinides (1991), and Ferson and Harvey (1992) for major studies). However, studies showing that asset returns are predictable using some predetermined variables have considerably stimulated tests of conditional asset pricing models for beta-pricing models including the CAPM of Sharpe (1964), Lintner (1965), and Black (1972), Arbitrage Pricing Theory (APT) of Ross (1976), and multi-beta models based on investor optimization and equilibrium by Merton (1973), Breeden (1979), and Cox, Ingersoll, and Ross (1985).

Major studies reporting the predictability of both short and long-term asset returns include Keim and Stambaugh (1986), Campbell (1987), Campbell and Shiller (1988), Fama and French (1988a, 1988b, 1989), Lo and MacKinlay (1988), Fama (1990) and Conrad, Gultekin, and Kaul (1991). Reviewing these studies, Fama (1991) interprets common variation in predicted returns across various assets as consistent with the rational asset pricing theory.

Hansen and Hodrick (1983) and Gibbons and Ferson (1985) have developed latent-variable-model tests of asset pricing models by focusing on time-varying expected returns. Harvey (1989), Ferson (1990) and Ferson, Foerster, and Keim (1993) further extend tests of latent variable models. The general message from the tests of latent variable models is that only a few common factors are needed to explain the cross-section of expected returns. Ferson and Harvey (1991) and Ferson and Korajczyk (1995) examine conditional multi-beta pricing models and provide evidence that the predictability of asset returns can be well explained by the conditional multi-beta pricing models. The time-variation of the second moments are also incorporated into testing of conditional asset pricing models. Generally, asset pricing models imply restrictions on the conditional first and second moments of returns. The autoregressive conditional heteroscedasticity in mean (ARCH-M) by Engle, Lilien, and Robbins (1987) and GARCH-M models have been used to test the restrictions. Major studies examining the ARCH-M type models of asset pricing include Bollerslev, Engle, and Wooldridge (1988), Engle, Ng, and Rothschild (1992), and Buse, Korkie, and Turtle (1994).

In an international setting, several studies have examined the time-varying expected returns and conditional asset pricing models. Harvey (1991) tests the conditional version of the Sharpe (1964) and Lintner (1965) CAPM by using data on the monthly equity indices for 17 countries over the period 1970-1989. The instrumental variables approximating the conditioning information include both common and local variables such as the lagged excess returns, January dummy, the dividend yields, the term structure premia and the default risk premia. The results indicate that the world CAPM can describe adequately the cross-sectional variation in returns across different countries, except for Japan. He suggest the possibility that Japan is not fully integrated with the world market.

Chan, Karolyi, and Stulz (1992) (henceforth CKS) examine a conditional version of the world CAPM by using data on the daily U.S. and foreign equity market returns over the period 1978-1989. Using the world CAPM and the definition of the covariance, CKS present the model in which the expected returns on the U.S. equity market are affected by the covariance with the foreign markets and its own variance. The second moments of the returns are specified to vary over time with a multivariate GARCH model of Engle and Kroner (1995). They find that the U.S. equity market is significantly influenced by the foreign market. This result is robust to a number of alternative specifications and different measurement intervals. They interpret the significant influence of the foreign market on the U.S. market as consistent with the global integration of the U.S. market. Further, the restrictions implied by the world CAPM are not rejected.

Ferson and Harvey (1993) examine conditional versions of single-beta and multi-beta pricing models, using data on the monthly index returns for 18 countries over the period 1970-1989. They investigate the issue of how the predictability of national equity market returns is related to the global economic risk. The results indicate that the multi-beta pricing models can capture much of the predictability of national equity market returns for many countries. Furthermore, they find that the major component of the predictability in returns is the time-varying global risk premia. Ferson and Harvey (1996) also investigates the issue of whether predetermined attributes of stocks such as ratios of price-to-book-value, cash-flow, and earnings are related to exposures to economic risk factors by using data on monthly national equity returns for 21 countries. The level of analysis is an individual country, and their single and two-factor models allow the attributes at the country level to affect the expected national equity returns through the influences of the attribute on the risk exposures. The results indicate that the cross-sectional predictive power of the attributes is related to both risk and mispricing, but the influences of the attribute on the risk exposures are more important than mispricing.

Dumas and Solnik (1995) examine the conditional version of Adler and Dumas' (1983) international asset pricing model in which the exchange-rate risk, as well as the covariance with the world market portfolio, is priced due to the deviations from the purchasing power parity. Their model is applied to data on the monthly equity indices for four countries, deposits for three currencies, and proxy for the world market portfolio over the period 1970-

1991. The results indicate that the foreign-exchange risk premia are a significant component of asset returns in the world financial market.

Campbell and Hamao (1992) use a latent-variable-model approach to investigate the long-term integration of the U.S. and Japanese equity markets. Using data on the monthly U.S. and Japanese equity indices over the period 1971-1990, they examine a single-latent-factor model with constant betas, which implies the perfect correlation between the expected returns on the U.S. and Japanese markets under the integration. The results from the latent-variable tests indicate that a single factor model is inconsistent with the data. However, they provide evidence for the common movements of the expected returns between the U.S. and Japanese markets, which are consistent with the partial integration of both markets.

The reviewed studies have shown that the behaviour of asset returns across countries is consistent with the time-varying expected returns implied by the international asset pricing models. Since most tests of the international asset pricing models are a joint test of an model and market integration, evidence for the international asset pricing models also supports integration. Empirical results in the reviewed studies appear to be somewhat more favourable to a multi-factor model than a single-factor model at least for monthly data. However, CKS (1992) do not reject the world CAPM for daily data, which is a single-factor model.

Considering that the technical trading rules are applied to daily data, the model of CKS seems to be attractive to this thesis for a number of reasons. First, in their study, the conditional world CAPM is not rejected. Second, CKS's model explicitly takes into account a nonlinearity found in high frequency data, the conditional heteroscedasticity (Bollerslev, Chou, and Kroner 1992) by relating the expected returns to the time-varying second moments. Third, CKS's model implemented with daily data does not require macroeconomic variables as the conditioning information, unlike other studies. Most macroeconomic variables used in other studies (for example, Harvey (1991)) are not readily available on a daily basis.

2.3 Evidence on market segmentation

Stulz (1995) reviews studies which have developed theoretical models that explicitly specify the impact of barriers to international investment on asset pricing. Investment barriers due to high transaction costs, government-imposed controls on foreign exchange and capital flow, differential taxes, and information costs may lead to segmented capital markets. Black (1974) is among the pioneers whose work is on the effects of international investment barriers on asset pricing. Stulz (1981b) examines the same issue in a more generalized framework. Errunza and Losq (1985) examine asset pricing relation under the assumption that securities from a country are not available to foreign investors, but investors from that country can invest abroad. They call market segmentation caused by such one-way investment barriers "mild segmentation."

Evidence for segmentation has been provided by many studies. Stehle (1977) investigates the issue of market integration and segmentation by separating the national risk from the international risk under the null hypotheses of both integration and segmentation. Jorion and Schwartz (1986) examine the issue of integration versus segmentation for the Canadian equity market over the period 1963-1982. They provide evidence that the Canadian market is segmented relative to the U.S. market. Mittoo (1992) examine the integration of the Canadian and U.S. equity markets. She finds that the results are consistent with segmentation in the 1977-1981 subperiod, but integration in the 1982-1986 subperiod. Karolyi (1995) examines transmissions of stock returns and volatility between the U.S. and Canada by using the bivariate GARCH model with daily index data over the period 1981-1989. The observed transmission pattern is different between the stocks that are interlisted in both countries and listed only in Canada. This result indicates that some investment barriers between both countries are effective.

Cho, Eun, and Senbet (1986) test the Arbitrage Pricing Theory (APT) of Ross (1976) which is extended to an international setting by Solnik (1983), with data on individual stocks in eleven countries over the period the 1973-1983. Their results reject the joint hypothesis that the international markets are integrated and that the international APT is valid. Gultekin, Gultekin, and Penati (1989) examine the effects of Japan's liberalization of capital flow in 1980 on the asset pricing relation in the Japanese and U.S. markets by using the APT as a benchmark model. Their results indicate that before the liberalization, the prices of risk are different between Japan and U.S., indicating segmentation before the liberalization.

Errunza and Losq (1985) test implications of the asset pricing relation under mild segmentation, using data on monthly stock returns in the U.S. and less developed countries over the period 1976-1980. Their empirical results are inconclusive. Errunza, Losq, and Padmanabhan (1992) test the complete integration, mild segmentation and complete segmentation hypotheses, using data on monthly stock returns in the U.S. and emerging markets over the period 1975-1987.They find that the stock returns in many emerging markets are consistent with the mild segmentation. Bae (1995) tests a conditional version of Errunza and Losq's (1985) model for the Korean equity market by using data on weekly equity market index returns over the period 1980-1990. He finds that the structure of the Korean equity market is consistent with the predictions of the mild segmentation hypothesis.

Harvey (1995) examine risk and returns in emerging markets by using data on monthly returns of emerging markets over the period 1976-1992. The results indicate that own-country standard deviation can explain the cross-section of unconditional returns better than a standard global asset pricing model, indicating the segmentation of emerging markets. Furthermore, the patterns in the predictability of returns on emerging markets are inconsistent with the conditional global asset pricing models. Bekaert and Harvey (1995) investigate the issue of market integration and segmentation for emerging markets by extending the CKS (1992) model. They find that a number of emerging markets experience time-varying integration. Bekaert and Harvey (1997) examine the volatility of emerging markets by using the same model as Bekaert and Harvey (1995). They find that capital market reforms increase the correlation of emerging markets with the world market but do not increase the volatility of emerging markets.

2.4 Asset pricing under mild segmentation

Complete market integration and complete segmentation are two extremes of possible international capital market structure. Alternatively, Errunza and Losq (1985) have proposed a middle-ground type of market structure as a more realistic international environment than those assumed in other studies.

Errunza and Losq (1985) examine international asset pricing under the specific form of imperfection in which a class of investors can not trade in a subset of securities, while the others can trade in all the securities available. This kind of imperfection may become relevant when capital inflow restrictions are imposed by national governments. They name the international market structure caused by this type of imperfection "mild segmentation."

In a two-country setting, Errunza and Losq (1985) assume that investors in country 1 (restricted investors) can trade only in securities in country 1, while investors in country 2 (unrestricted investors) can trade in all securities available. Securities in country 1 are termed eligible securities. Ineligible securities can be held only by the investors in country 2. This assumption means that the capital inflow restrictions imposed by the government of country 2 prevent investors in country 1 from holding country 2 securities. Further, they assume that investors are mean-variance optimizers in terms of the real return and that the real returns on securities follow the multivariate normal distribution. Under these assumptions, the theoretical model of Errunza and Losq (1985) implies that the expected returns on ineligible securities (country 2 securities) are determined jointly by both international and national risk premiums, while the expected returns on eligible securities (country 1 securities) are determined only by the international risk premium in the same way as the world CAPM. The national risk premium on the ineligible securities is interpreted as a "super risk premium" commanded by investors in country 2 to absorb the supply of the ineligible securities which only they can hold. Later, Errunza and Losq (1989) extend their theoretical model to a multi-country setting and examine implications of the model for economic welfare.

2.5 Summary

Early studies find that technical analysis is not profitable. However, recent studies such as BLL (1992) and Bessembinder and Chan (1995) have shown that some simple technical trading rules can predict future returns and possibly are profitable.

Although time-varying expected returns are a possible explanation for the technical rule profits, none of the studies examining technical trading rules for stock markets have directly tested a conjecture that the trading rules capture time-varying expected returns on stocks implied by equilibrium asset pricing models. Thus, an important contribution of this thesis is to evaluate technical trading rules for stock markets by using as a benchmark model the equilibrium asset pricing models which allow for time-varying expected returns. For currency futures markets, Kho (1996) applies the bootstrap methodologies used by BLL (1992) to asset pricing models. Following Kho (1996) and BLL (1992), this thesis utilizes the bootstrap methodologies in assessing the trading rule profits.

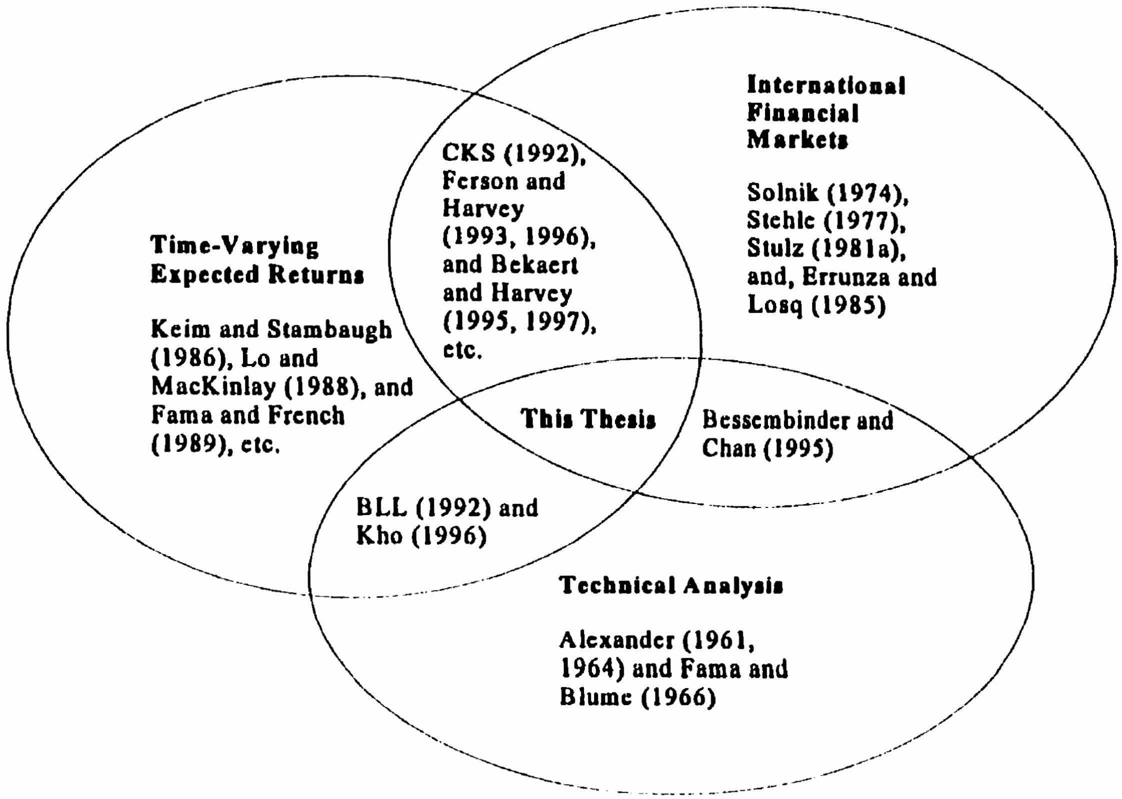
Bessembinder and Chan (1995) have brought an international context to the technical analysis literature by examining technical trading rules in several Asian equity markets. Although their results suggest a possible connection between the trading rule profits and market segmentation, they do not examine this connection in light of the asset pricing relation affected by the segmentation. Thus, another important contribution of this thesis is to examine the effects on the trading rule profits of market integration and segmentation by using asset pricing models corresponding to market integration and different degrees of market segmentation.

In an international setting, many studies have indicated that expected returns on national equity markets vary over time in a way consistent with international asset pricing models under integration (CKS 1992; Ferson and Harvey 1993, 1996; Bekaert and Harvey 1995, 1997). Among such studies, CKS's model seems to be attractive to this thesis for a number of reasons. First, in their study, the conditional world CAPM is not rejected. Second, CKS's model incorporates the conditional heteroscedasticity frequently observed in daily data (Bollerslev, Chou, and Kroner 1992). Third, their model implemented with daily data does not require macroeconomic variables, most of which are not readily available on a daily basis.

The literature has not unanimously agreed that the world financial market is integrated (Stulz 1995). In fact, many studies have indicated that capital markets are somehow segmented. Errunza and Losq (1985) have examined the asset pricing relation under a continuum of two extreme market structures, complete integration and complete segmentation. Their model is called the asset pricing model under "mild segmentation." This thesis utilizes the intuition of their model as well as the implications of complete segmentation to examine the effects on the trading rule profits of market segmentation.

As a summary of the literature review, the schematic positioning this thesis among past studies is presented in Figure 1. The contribution of this thesis lies in an intersection of the literature on technical analysis (Alexander 1961, 1964; Fama and Blume 1966), international financial markets (Solnik (1974), Stehle (1977), Stulz (1981a) and Errunza and Losq (1985) for major studies), and time-varying expected returns (Keim and Stambaugh (1986), Lo and MacKinlay (1988), and Fama and French (1989) for major studies). Among the three steams of literature, the technical analysis literature has been only separately linked with the other streams of literature. Specifically, BLL (1992) and Kho (1996) connect technical analysis with the literature on time-varying expected returns without taking into account issues relevant to an international asset pricing context such as investment barriers and resulting market segmentation. On the other hand, although Bessembinder and Chan (1995) extend

Figure 1
Positioning of this thesis



the examinations of technical analysis to the international sample, their study does not incorporate the growing literature on international financial markets and asset pricing that explicitly takes into account time-varying expected returns (Harvey 1991; CKS 1992; Campbell and Hamao 1992; Ferson and Harvey 1993, 1996; Bekaert and Harvey 1995, 1997). Thus, this thesis is the first study that incorporates all three streams of literature.

Chapter 3 Standard Tests of Technical Trading Rules

This thesis applies standard test statistics to technical trading rules in order to evaluate the profitability of the trading rules before turning to bootstrap tests. In addition, the effects of transaction costs on the trading rule profits are examined, since the earlier studies (Alexander 1964; Fama and Blume 1966) conclude that technical rules are not profitable relative to the buy and hold when transaction costs are taken into account. This chapter explains the details of technical trading rules to be examined, the methodologies of standard test to be used, and how to examine the effects of transaction costs.

3.1 Technical trading rules

This thesis examines the same set of trading rules as BLL use. If this thesis uses new trading rules that are found "profitable" by this thesis, some serious concern may arise due to data-snooping biases. The data-snooping biases occur if test statistics are affected by the empirical relations uncovered in the vary same data that the test statistics are applied to (Lo and MacKinlay 1990b). The new trading rules may exhibit apparently significant forecast power simply because the same data are used to test the new rules. As BLL stress, in such a case, there is the great danger that researchers may mistakenly conclude significant trading rule profits because of the data-snooping biases.

This thesis examines three different groups of technical trading rules: variable-length moving average (VMA) rules, fixed-length moving average (FMA) rules and trading range break (TRB) rules. These technical trading rules should be considered to be forecasting rules which classify every day into buy or sell ahead of time by using the information on the past prices. Therefore, the technical trading rules can lead to a specific trading strategy only when buy and sell signals are connected with specific trading behaviour. As BLL suggest, the technical trading rules are often associated with a trading strategy where investors go long if buy signals are generated and short if sell signals are generated.

The VMA rules generate signals by comparing a short-term moving average of prices to a long-term moving average of prices. The use of moving averages attempts to smooth out the noise in the price series. The crossing of the two moving averages is considered to indicate the initiation of a trend in the price. Specifically, buy (sell) signals are generated when the short-term average exceeds (falls below) the long-term average by at least a prespecified band. If the short-term average falls inside the upper and lower bands around the long-term average, no signal is generated. If the band of 0% is used, the VMA rules classify all days into either buy or sell days. The idea behind using a band is to avoid the emission of "spurious" signals when the short-term and long-term averages are close to each other. Following BLL, this thesis evaluates the five variations of this rule, (1, 50), (1, 150), (5, 150), (1, 200) and (2, 200), where the first number in the parentheses denotes the number of days for the short-term moving average and the second number denotes the number of days for the long-term moving average. Further, each rule is evaluated with the bands of 0 and 1%, making for 10 individual rules in total.

Similar to the VMA rules, the FMA rules generate buy (sell) signals when the short-term moving average of prices exceeds (falls below) the long-term moving average of prices by at least a prespecified band. If the short-term average falls inside the upper and lower bands around the long-term average, no signal is generated. The FMA rules implicitly assume that returns should be different for a few days after the short-term average crosses the long-term average or the bands of the long-term average. Thus, if signals are generated, the FMA rules require investors to stay in the same position (i.e., either buy or sell) for a fixed number of days, ten days in this thesis, by following BLL. Other signals generated during this ten-day period are ignored. When the ten-day period passes, the FMA rules start to react to new signals. Following BLL, this thesis evaluates the five variations of this rule, (1, 50), (1, 150), (5, 150), (1, 200) and (2, 200), where the first number in the parentheses denotes the number of days for the short-term moving average and the second number denotes the number of days for the long-term moving average. Further, each rule is evaluated with the bands of 0 and 1%, making for 10 individual rules in total.

The TRB rules generate signals by comparing the current price to the recent minimum and maximum of prices. The TRB rules generate buy signals when the current price exceeds the recent maximum (the resistance level) by at least a prespecified band. The rationale for this rule is that when the current price reaches the previous peak, a great deal of selling pressure arises because many people would like to sell at the peak. Therefore, the previous peak of the prices tends to form the resistance level. However, if the price exceeds the previous peak, it is indicated that the resistance level has been broken out and that the upward trend in the price has been initiated. The purpose of using a band is to avoid the emission of "spurious" signals. On the other hand, the TRB rules generate sell signals when the current price falls below the recent minimum (the support level) by at least a prespecified band. The rational is that when the current price reaches the previous minimum, a great deal of buying pressure arises because many people would like to buy at the minimum price. Therefore, the previous minimum tends to form the support level. However, if the price falls below the previous minimum, it is indicated that the support level has been penetrated and that the downward trend has been initiated. Similar to the FMA rules, if new signals are generated, the TRB rules require investors to stay in the same position (i.e., either buy or sell) for a fixed number of days, ten days in this thesis, by following BLL. Other signals generated during this ten-day period are ignored. When the ten-day period passes, the TRB rules start to react to new signals. This thesis evaluates the TRB rules where recent maximums and minimums are defined as the extreme observations over the prior 50, 150, and 200 days, respectively. Further, each rule is evaluated with the bands of 0 and 1%, making for 6 rules in total.

The VMA, FMA and TRB rules are applied to daily equity indices in various countries. All trading rule signals are obtained, based on the closing prices of the indices. Using the information on the past prices, each trading rule classifies all days into buy, sell or neutral (days when no signals are generated). The return conditional on a specific signal is calculated as follows. If a buy (sell) signal is generated at the close of day t-1, the next day, day t, is classified as a buy (sell) day. The return on day t conditional on the buy (sell) signal which is observed at the close of day t-1 is calculated from the closing price of day t-1 to the closing price of day t. Daily returns are defined as differences of logarithm of subsequent closing prices. This method for calculating the conditional return implicitly assumes that if a new signal is generated at the close of day t-1, a hypothetical investor executes trades immediately at the closing price of day t-1.

This thesis also reports the conditional trading-rule returns which would be obtained if an investor kept a one-day lag between the initial emission of a signal and the subsequent trade. As Bessembinder and Chan (1995) discuss, the spurious positive autocorrelation resulting from the nonsynchronous trading of component securities in the equity index may cause the technical trading rules to appear profitable. The technical rules tend to generate a buy or sell signal initially on a day which experiences a large price movement. Delay in reflecting such a large movement on the index value due to the nonsynchronous trading implies that the measured return on a next day is likely to be biased in the same direction as the return on the day of a large price movement. Thus, signals emitted by the technical rules may spuriously exhibit forecast power. In order to take into account the effects of the nonsynchronous trading, this thesis simply computes the conditional buy and sell returns based on trades executed with a one-day lag after the initial emissions of signals.[2] If the trading rule returns with a one-day lag reduce the profits obtained with a zero-day lag considerably, it may be inferred that the technical rule profits are attributable to the nonsynchronous trading.

[2] Bessembinder and Chan (1995) examine trading rule profits with a one-day lag to take into account nonsynchronous trading.

3.2 Methodologies for standard test statistics

Three groups of technical trading rules, VMA, FMA and TRB, are applied to daily equity market indices in this thesis. The conditional mean and standard deviation of trading rule returns are computed for individual trading rules. Based on the price information up to the close of day t-1, the trading rules classify each next day, day t, as either buy (b), sell (s) or neutral (n). The mean return and standard deviation conditional on buy signals over the sample of the total N days including buy, sell and neutral days are defined as follows:

The conditional mean return:

$$\mu_b = \frac{1}{N_b} \sum_{t=1}^{N} R_t \, I_{t-1}^{b} , \tag{1}$$

The conditional standard deviation:

$$\sigma_b = \left[\frac{1}{N_b - 1} \sum_{t=1}^{N} (R_t - \mu_b)^2 \, I_{t-1}^{b} \right]^{\frac{1}{2}} , \tag{2}$$

where: N_b = number of buy days, which is by definition $\leq$ N,

R_t = daily index return, and

I_{t-1}^{b} = indicator function taking a value equal to one for a buy signal observed on day t-1 and zero otherwise.

That is, the mean return conditional on buy signals or more simply the mean buy return is calculated as the average daily return over the sub-sample consisting of the days for which buy signals are generated. The mean return, μ_s, and standard deviation, σ_s, conditional on sell signals are defined in a similar way. The difference between the mean buy and sell returns, $(\mu_b - \mu_s)$, is referred to as the buy-sell spread in this thesis.

Significance in the deviation of the conditional mean return from the unconditional mean return is evaluated, using OLS regression test for timing ability, suggested by Cumby and Modest (1987). The Cumby-Modest regression test can take into account the heteroscedasticity in returns when calculating test statistics. Further, it allows us to test the joint hypothesis that the trading rules have no forecast power across all individual rules.

For each trading rule, the following regression is run:

$$R_t = a_0 + a_1 X_{t-1} + \varepsilon_t \, , \tag{3}$$

where R_t is the equity index return on day t and X_{t-1} is the trading signal observed on day t-1. This thesis runs three variations of regression (3) corresponding to the buy signal, sell signal and buy-sell spread to test whether each signal forecasts the next day's return correctly. For the regression which tests the forecast power of buy signals, a value of the indicator function, I^b_{t-1}, is used for X_{t-1}. That is, X_{t-1} is equal to one if a buy signal is generated at day t-1, and otherwise zero. The OLS is applied to regression (3), using the sample of the equity index returns over all N days including buy, sell and neutral days. In this regression, a positive estimate of a_1 indicates an average increase in daily returns due to correct buy signals. Therefore, testing for the difference between the conditional mean buy return and the unconditional mean return is equivalent to testing for the null hypothesis that $a_1 = 0$. In order to test the null hypothesis, White's (1980) heteroscedasticity-consistent t-statistic is calculated.

For the regression which tests the forecast power of sell signals, a value of the indicator function, I^s_{t-1}, is used for X_{t-1}. That is, X_{t-1} is equal to one if a sell signal is generated at day t-1, and otherwise zero. Again, the OLS is applied to regression (3), using the sample of the equity index returns over all N days. A negative estimate of a_1 indicates an average decrease in daily returns due to correct sell signals. Therefore, testing for the difference between the conditional mean sell return and the unconditional mean return is equivalent to testing for the null hypothesis that $a_1=0$. White's (1980) heteroscedasticity-consistent t-statistic is used to test the null hypothesis.

For the regression which tests the average spread between the buy and sell returns, the difference between values of the two indicator function, $I^b_{t-1}-I^s_{t-1}$, is used for X_{t-1}. That is, X_{t-1} is equal to one if a buy signal is generated at day t-1, minus one if a sell signal is generated, and zero if no signal is generated. Regression (3) is run, using the sample of the equity index returns over all N days. Thus, a positive estimate of a_1 indicates an average increase of the buy returns over the sell returns. Therefore, testing for the difference between the conditional mean buy and sell returns is equivalent to testing for the null hypothesis that $a_1=0$. White's (1980) heteroscedasticity-consistent t-statistic is used to test the null hypothesis.

For each of the three trading rule groups, this thesis calculates Wald test statistics testing whether all slope coefficients in regression (3) are jointly zero across individual rules in a way that takes account of cross-rule dependencies. For each trading rule group, the joint test is applied separately to the buy signal, sell signal, and buy-sell spread. Specifically, regressions corresponding to individual rules are stacked to calculate a heteroscedasticity-consistent estimate of the covariance matrix of the system of equations. The usual χ^2 statistic for the joint hypothesis that all values for a_1 are zero across individual rules is calculated, with the degree of freedom equal to the number of individual rules being stacked. For example, for the buy signals generated by the VMA rules, the joint hypothesis that all values for a_1 are jointly zero across individual rules is tested as follows: since the group of the VMA rules includes ten individual rules, the ten regressions which regress the equity index returns on the indicator functions of buy signals are stacked to form the system of the ten regression equations; using a set of residuals obtained from the ten regressions, the heteroscedasticity-consistent estimate of the covariance matrix for the estimates of the slope coefficients is calculated;. a linear restriction implied by the joint hypothesis is applied to the estimated covariance matrix, and the calculated Wald test statistic is distributed as χ^2 with the degree of freedom equal to ten.

3.3 Examples for trading signals

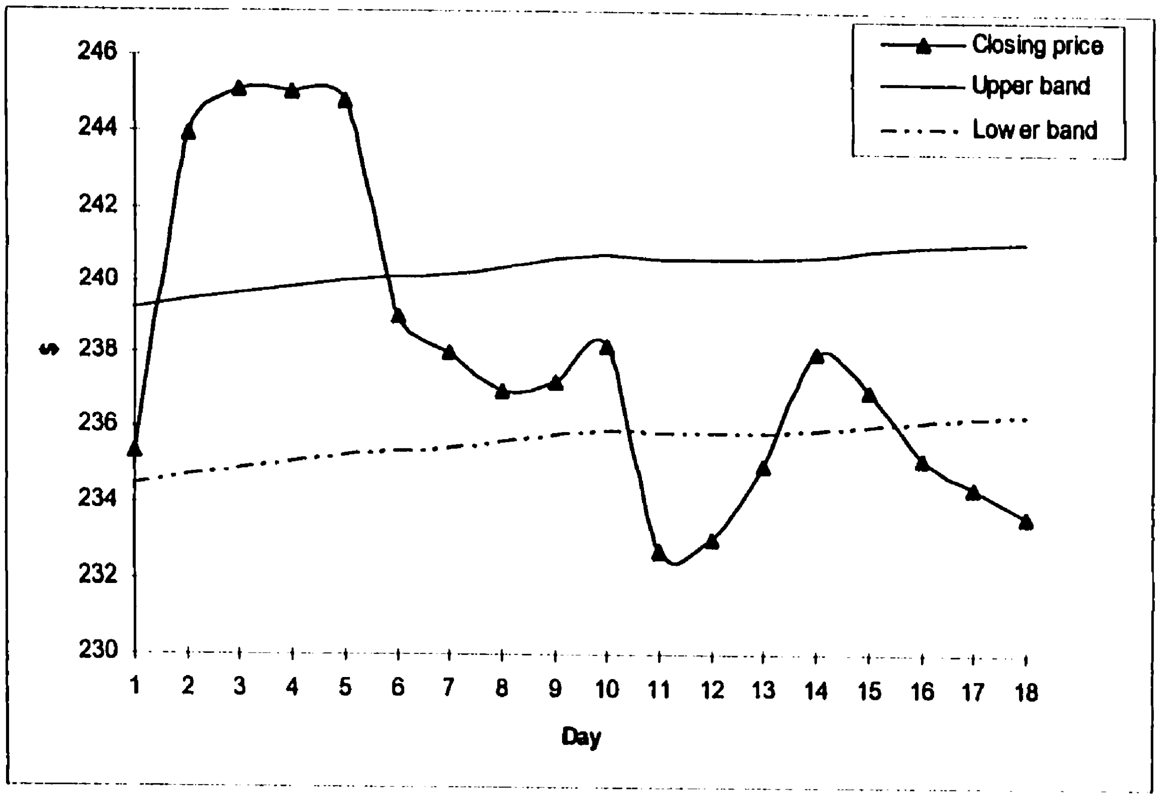
In this section, simple examples are explained to illustrate how each of the VMA, FMA and TRB generates signals.

First, suppose that in order to obtain signals, an investor uses one of the VMA rules, (1, 50, 0.01), where the short-term moving average is 1 day, the long-term moving average is 50 days, and the band is 1%. At the close of every day, the closing price is considered to be the short-term moving average, and the investor calculates the 50-day average of the most recent closing prices as the long-term moving average. If the short-term moving average is 5 days as in VMA(5, 150, 0.01), the investor calculates the 5-day average of the most recent closing prices as the short-term moving average. The use of a 1% band means that a buy (sell) signal is generated if the short-term average exceeds (falls below) the long-term average by at least 1%. Therefore, at the close of every day, the investor needs to calculate the upper band which is defined as the long-term average times 1.01. Similarly, the investor needs to calculate the lower band which is defined as the long-term average times 0.99. Thus, under VMA(1, 50, 0.01), if the current price exceeds the upper band at the close of the market, a buy signal is generated for the next day, and if the current closing price falls below the lower band at the close of the market, a sell signal is generated for the next day. If the current closing price falls inside the upper and lower bands at the close of the market, no signal is generated for the next day.[3]

Figure 2 depicts the movements of the closing price, upper band, and lower band over the

[3] If the band is 0%, the long-term average and the upper and lower bands are all the same. Consequently, new signals are generated whenever the short-term average crosses the long-term average, and all days are classified into either buy or sell days.

Figure 2
Example for trading signals: VMA(1, 50, 0.01) and FMA(1, 50, 0.01)



period from day 1 to day 18, based on the VMA(1, 50, 0.01). The actual data on the daily Canadian equity index are used to draw this graph. At the close of day 1, the closing price falls inside the upper and lower bands. Therefore, no signal is generated for the next day, day 2. At the close of day 2, the closing price exceeds the upper band. Thus, a buy signal is generated for the next day, day 3. The return of day 3 from the closing price of day 2 to the closing price of day 3 is called the return on day 3 conditional on the buy signal observed at the close of day 2. After day 3, this buy signal is effective until the closing price (i.e., short-term average) crosses the upper or lower band again. This occurs on day 6. At the close of day 6, the closing price falls inside the upper and lower bands for the first time after day 3. Thus, the buy signal generated at the close of day 2 is terminated, and no signal is generated for the next day, day 7. In other words, day 7 is classified as "neutral." The next crossover occurs on day 11. At the close of day 11, the closing price falls below the lower band for the first time after day 7. Thus, a sell signal is generated for the next day, day 12. This sell signal is effective until the next crossover occurs, which corresponds to the close of day 14 in this figure. At the close of day 14, the closing price falls inside the upper and lower bands. Therefore, the sell signal is terminated and the next day, day 15, is classified as "neutral." At the close of day 16, the closing price falls below the lower band again, and a new sell signal is generated for the next day, day 17. Day 18 is also classified as sell in this figure. During this 18-day period, buy signals are generated for day 3 to day 6; thus, the mean return conditional on buy signals is calculated as the average daily return over this 4-day subperiod. On the other hand, sell signals are generated for day 12 to day 14 and day 17 to day 18 (5 days in total); thus the mean return conditional on sell signals is calculated as the average daily return over this 5-day subperiod. The buy-sell spread is calculated as the mean return conditional on buy signals minus the mean return conditional on sell signals. The conditional standard deviation is calculated in a similar way.

To illustrate how the FMA rules generate signals, Figure 2 is used again. Suppose that in order to obtain signals, an investor uses FMA(1, 50, 0.01), where the short-term moving average is 1 day, the long-term moving average is 50 days, and the band is 1%. At the close of every day, the upper and lower bands are calculated in the same way as VMA(1, 50, 0.01). The difference between the FMA and VMA rules is that the FMA rules require the investor to stay in the same position (either buy or sell) for the next 10 days after a signal is generated. Figure 1 indicates that at the close of day 2, the closing price exceeds the upper band. Thus, a buy signal is generated for the next day, day 3. This buy signal is effective for the next 10 days, i.e., until the close of day 12. This means that the two crossovers which occur at the closes of day 6 and day 11 are ignored and that buy signals are kept until the close of day 12. At the close of day 12, FMA(1, 50, 0.01) starts to react to a new signal. Since the closing price is lower than the lower band on day 12, a sell signal is generated for the next day, day 13. This sell signal is effective for the next 10 days, i.e., until day 22. Since the sample period in this example ends on day 18, the sell signals are kept for the remaining 6 days (day 13 to day 18). In this example, FMA(1, 50, 0.01) generates buy signals for day 3 to day 12 (10 days in total); thus, the mean return conditional on buy signals is calculated as the average daily return over this 10-day subperiod. On the other hand, sell signals are generated for day 13 to day 18 (6 days in total); thus the mean return conditional on sell signals is calculated as the average daily return over this 6-day subperiod. The buy-sell spread is calculated as the mean return conditional on buy signals minus the mean return conditional on sell signals. The conditional standard deviation is calculated in a similar way.

The last example is provided for the TRB rules. Suppose that in order to obtain signals, the investor uses TRB(50, 0.01), where the recent maximum and minimum are defined as the extreme observations over the prior 150 days, and the band is 1%. At the close of every day, the investor compares the current closing price with the recent maximum and minimum over the prior 150 days. The 150-day period does not include the current day on which comparisons are made to generate a signal for the next day. The band of 1% is used as follows. If the current price exceeds the resistance level which is defined as the recent maximum times 1.01, a buy signal is generated for the next day. On the other hand, if the current price falls below the support level which is defined as the recent minimum times 0.99, a sell signal is generated for the next day. If the current closing price falls inside the resistance and support levels, no signal is generated for the next day. Similar to the FMA rules, the TRB rules require the investor to stay in the same position (either buy or sell) for the next 10 days after a new signal is generated. Other signals generated during the 10-day period are ignored. When the 10-day period passes, the TRB rules start to react to new signals.[4]

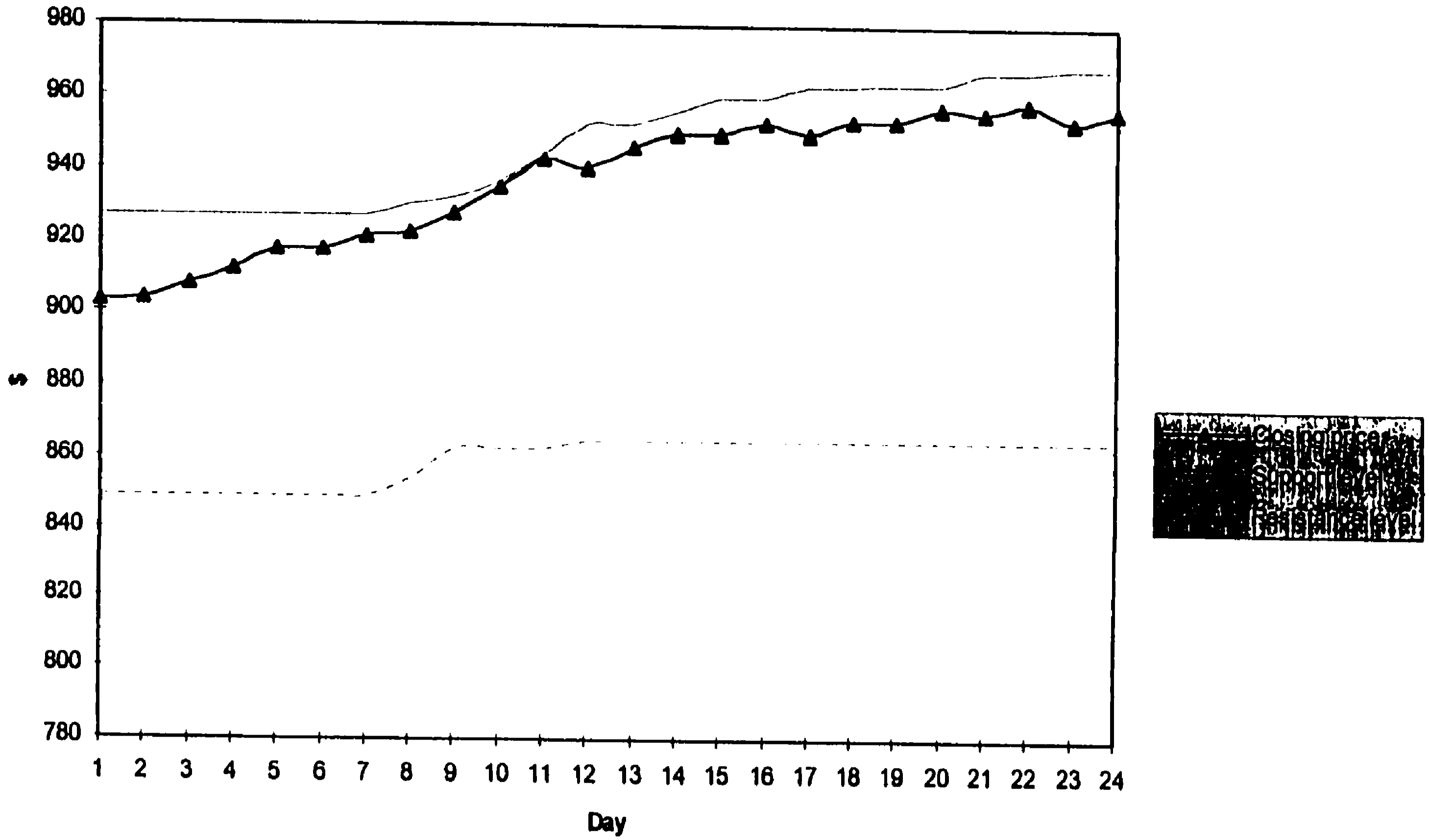
Figure 3 depicts the movements of the closing price, resistance level, and support level over the period from day 1 to day 24, based on TRB(50, 0.01). At the close of day 1, the closing price falls inside the resistance and support levels. Therefore, no signal is generated for the next day, day 2. In other words, day 2 is classified as "neutral." Since the closing price stays inside the resistance and support levels until the close of day 10, all 10 days from day 2 to day 11 are classified as "neutral." At the close of day 11, the closing price exceeds the resistance level for the first time. Thus, a buy signal is generated for the next day, day 12. This buy signal is effective for the next 10 days, i.e., until the close of day 21. Any signals generated during the period from day 12 to day 21 are ignored. Since the closing price falls inside the resistance and support levels at the close of day 21, no signal is generated for the next day, day 22. The closing price stays inside the resistance and support levels until the end of the sample period. Thus, day 22 to day 24 are classified as "neutral.' In this example, buy signals are generated for the 10-day subperiod from day 12 to day 21, and no sell signals are generated. The mean return conditional on buy signals are calculated as the average daily return over the subperiod from day 12 to day 21.

3.4 Consideration of transaction costs

Technical trading rules can be profitable to the extent to which the profits are just eliminated by the transaction costs that the trading rules incur, under the version of market efficiency

[4] If the band of 0% is used, the resistance level is equal to the recent maximum, and the support level is equal to the recent minimum.

Figure 3
Example for trading signals: TRB(50, 0.01)



which is re-stated by Fama (1991). In fact, the earlier studies on technical analysis (Alexander 1964; Fama and Blume 1966) conclude that technical analysis is not profitable relative to the buy-and-hold strategy when transaction costs are taken into account.

This thesis provides some information on the effects of transaction costs on the trading rule profitability by comparing returns on the "double-or-out" strategy with returns on the buy-and-hold strategy. There are several motivations for the use of this strategy. The double-or-out strategy does not require investors to go short when a sell signal is emitted. This feature may be important because short sales are severely restricted by national governments for some countries. In addition, since Bessembinder and Chan (1995) use the double-or-out strategy to evaluate the trading rule profits, the use of the same trading strategy will facilitate comparison between results in this thesis and their study.

Specifically, if a buy signal is emitted, the double-or-out strategy requires an investor to borrow additional fund at an interest rate in order to increase a long position in the equity index by 100%. For example, an investor initially holding \$100 will borrow \$100 at the interest rate and invest the total \$200 in the equity index if a buy signal is emitted. This results in a pre-transaction-cost trading rule return on a buy day of $TR_t = 2R_t - r_t$, where R_t is the equity index return and r_t is the daily interest rate. If a sell signal is emitted, the strategy requires an investor to liquidate any equity position and invest in the interest bearing asset. This results in the trading rule returns on a sell day of $TR_t = r_t$. On days classified as neutral, the strategy simply holds a long position in the equity index, leading to the trading rule returns of $TR_t = R_t$. The additional return, π, earned by technical trading rules relative to the buy-and-hold strategy prior to transaction costs is given as:

$$\pi = \Sigma TR_t - \Sigma R_t \ . \tag{4}$$

This is equivalent to the additional terminal wealth over the buy-and-hold strategy, per currency unit initially invested, of using the double-or-out strategy.

In reality, the double-or-out strategy would incur transactions costs. This thesis calculates a break-even transaction cost by following Bessembiner and Chan (1995). Let C denote the percentage round-trip cost of buying and selling the equity index. In this context, buying (selling) the index means buying (selling) a basket of individual stocks in the index. Therefore, the transaction cost C for the index is interpreted as the average transaction cost for trading a basket of stocks in the index. On days when a buy or sell signal is initially emitted, the trading rule return is reduced by $C/2\%$. When the position is subsequently closed out, the trading rule return is reduced by another $C/2\%$, leading to a total transaction cost of C for each emission of initial signals. The break-even transaction cost which equates the return on the double-or-out strategy with the return on the buy and hold is defined as:

$$C^* = \pi/(n_b + n_s), \tag{5}$$

where n_b and n_s are the number of days on which buy and sell signals are initially emitted, and their sum is the total number of the round-trip transactions that result from implementing the trading rule. The accumulated profit on the double-or-out strategy over the buy and hold at a prespecified level of transaction cost can be also obtained as $\pi - C(n_b + n_s)$.

Using data on equity indices and local interest rates in various countries, this thesis calculates the break-even transaction costs and the accumulated profits at various hypothetical levels of transaction costs for the technical trading rules to be examined. Results should shed some light on the economic significance of the trading rule profits under the existence of transaction costs.

Chapter 4 Asset Pricing Models and International Capital Market Structure

This thesis evaluates the profits on technical trading rules, using the conditional asset pricing models which allow for the time variation of the expected returns. The trading rules may be able to predict future returns to the extent to which signals emitted by the rules are correlated with the time-varying expected returns. In such a case, however, the apparent profits on the trading rules are not an indication of market inefficiencies but simply a fair compensation for the riskiness of the rules.

In an international asset pricing context, whether financial markets are integrated or segmented is an important issue because the form of pricing relation among assets will be substantially different (Stulz 1995). As the literature review in Chapter 2 suggests, there has been no unequivocal agreement about the issue of whether financial markets are integrated. Therefore, this thesis uses three different types of conditional asset pricing models corresponding to complete integration, "mild segmentation" by Errunza and Losq (1985), and complete segmentation to evaluate the technical rules.

This thesis incorporates the conditional asset pricing models under complete integration, mild segmentation and complete segmentation into a single conditional mean-variance framework. This framework can implies a set of the asset pricing models to be examined simply by changing an assumption about investment barriers, while generating sufficient implications to differentiate the asset pricing models. Specifically, complete integration assumes no investment barriers; under this assumption, expected returns on all securities and portfolios are determined by the world CAPM in which only the covariance with the world market portfolio is priced. Mild segmentation assumes one-way barriers against capital inflow from foreign countries, leading to the asset pricing model in which the covariance with the domestic (regulated) market, as well as the covariance with the world market portfolio, is priced for domestic securities (Errunza and Losq 1985). Finally, complete segmentation assumes two-way barriers, leading to the purely domestic CAPM in which only the covariance with the domestic market is priced for domestic securities. For the empirical implementation of the models, this thesis follows an approach taken by the CKS study which relates the expected returns to the conditional second moments that are to be estimated jointly with the expected returns, under a bivariate setting of the domestic versus foreign markets.

The use of the equilibrium asset pricing models under various capital market structures substantially differentiates this thesis from the study of BLL, who do not examine equilibrium models, and the studies of Kho (1996) and Bessembinder and Chan (1995), who do not explicitly consider the effects of market segmentation on the technical rule profits. It is worthwhile, however, to note that the purpose of this thesis is by no means a test of these asset pricing models; rather, under the conditional mean-variance framework, the asset pricing models corresponding to different market structures are used as a benchmark model whose simulated returns are compared with the actual returns on the trading rules.

4.1 Assumptions and setting

The conditional asset pricing models are estimated in a bivariate setting of the domestic versus foreign markets. The domestic market corresponds to the equity market in a country of interest, and the foreign market is defined as the equity market consisting of the rest of the world. The bivariate setting of the domestic versus foreign markets is applied separately to each of the countries which this thesis examines. For example, first, country A is defined as the domestic market; then the model is estimated using data on country A and foreign market returns, where the foreign market returns are defined as the returns on the portfolio consisting of all countries in the world except for country A. Next, country B is defined as the domestic market, and the model is estimated using data on country B and foreign market returns, where the foreign market returns are defined as the returns on the portfolio consisting of all countries in the world except for country B. The same procedure applies to each country to be examined. This approach makes it possible to conduct a country-by-country analysis. Although the cost of this approach is that cross-sectional restrictions are applied to only two markets at a time, it would be difficult to estimate the system of all counties to be examined because of an unusually large number of parameters.

This thesis makes the following common assumptions:

(A1) Investors are period-by-period mean-variance optimizers.

(A2) Investors's decisions are indifferent to the selection of the currency which is used to denominate their portfolio returns.

Assumption (A1) simply declares that this thesis follows a conditional mean-variance framework. Assumption (A2) implies that there is no exchange rate risk. The importance of exchange rate risk in international asset pricing has been discussed by Solnik (1974) and Stulz (1981a, 1983). As Adler and Dumas (1983) discuss, the issue of exchange rate risk can be simplified away if the purchasing power parity is assumed to hold or if all investors are assumed to have a logarithmic utility function. Although both assumptions are open to question, the absence of exchange rate risk is assumed for the tractability in this thesis. The focus of this thesis is on the effects of different market structures on trading rule profits rather than on the exchange rate risk that the trading rules would incur. Specifically, this thesis takes local investors' perspective, and all returns are denominated by the currency of the country which is defined as the domestic market. For example, when examining the Canadian equity market index as the domestic market, both the domestic and foreign returns are denominated by Canadian dollars; when examining the Japanese equity market index as the domestic market, all returns are denominated by yen. Returns are defined as differences of the logarithms of closing prices. An interest rate in the country which is defined as the domestic market is used as the riskless rate, and the excess returns for both domestic and foreign markets are defined as the raw returns minus the riskless rate.

The following assumptions correspond to three types of market structure, complete integration, mild segmentation and complete segmentation:

(A3) Complete integration:

There are no investment barriers. All securities traded in any markets are available to all investors.

(A4) Mild segmentation:

There are one-way investment barriers. While securities traded in the foreign markets are available to all investors, securities traded in the domestic market are available only to domestic investors.

(A5) Complete segmentation:

There are two-way barriers. There is no capital flow between the domestic and foreign markets.

Assumptions (A3), (A4) and (A5) lead to the world CAPM, the asset pricing model under mild segmentation and domestic CAPM, respectively.

4.2 Complete integration

Under the assumption of complete integration (assumption (A3)), the conditional version of the world CAPM holds. This thesis follows the empirical model of the world CAPM which CKS (1992) examine in their study.

CKS assumes that the aggregate relative risk aversion is constant over time. This assumption, as well as the common assumptions and assumption (A3), implies

$$E(r_{dt}|\Omega_{t-1}) = \lambda cov(r_{dt}, r_{mt}|\Omega_{t-1}) \ , \tag{6}$$

where:

r_{dt} = return on the domestic market portfolio in the excess of the riskless rate,

r_{mt} = return on the world market portfolio in the excess of the riskless rate,

Ω_{t-1} = information set available to investors at t-1,

λ = the aggregate relative risk aversion,

$E(\ |\ )$ = conditional expectation operator, and

$cov(\ |\ )$ = conditional covariance.

The excess return on the world market portfolio can be written as

$$r_{mt} = \omega_{dt-1} r_{dt} + (1-\omega_{dt-1}) r_{ft} , \tag{7}$$

where:

ω_{dt} = fraction of the domestic market portfolio relative to the world wealth, and

r_{ft} = return on the foreign market portfolio in the excess of the riskless rate.

Equations (6) and (7) lead to

$$E(r_{dt}|\Omega_{t-1}) = \lambda[\omega_{dt-1} var(r_{dt}|\Omega_{t-1}) + (1-\omega_{dt}) cov(r_{dt}, r_{ft}|\Omega_{t-1})] . \tag{8}$$

Equation (8) is the theoretical relation that CKS focus on. In order to implement the model empirically, they propose the bivariate system

$$r_{dt} = \alpha_d + \beta_{dv}\omega_{dt-1}h_{dt} + \beta_{dc}(1-\omega_{dt-1})h_{ct} + \theta_{d1}\varepsilon_{dt-1} + \theta_{d2}\varepsilon_{dt-2} + \varepsilon_{dt} , \tag{9a}$$

$$r_{ft} = \alpha_f + \beta_{fv}\omega_{ft-1}h_{ft} + \beta_{fc}(1-\omega_{ft-1})h_{ct} + \theta_{f1}\varepsilon_{ft-1} + \theta_{f2}\varepsilon_{ft-2} + \phi_f\varepsilon_{dt-1} + \varepsilon_{ft} , \tag{9b}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } \varepsilon_t = (\varepsilon_{dt}, \varepsilon_{ft})' \text{ and } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix} , \tag{10a}$$

$$H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon'_{t-1}A \ , \tag{10b}$$

where:

h_{dt}	=	conditional variance of the domestic market portfolio,
h_{ft}	=	conditional variance of the foreign market portfolio,
h_{ct}	=	conditional covariance of the domestic market portfolio with the foreign market portfolio,
ω_{dt}	=	fraction of the domestic market portfolio relative to the world wealth,
ω_{ft}	=	fraction of the foreign market portfolio relative to the world wealth,
H_t	=	2×2 conditional covariance matrix,
C	=	2×2 upper triangular matrix of parameters to be estimated,
A and G	=	2×2 matrices of parameters to be estimated,
ε_{dt} and ε_{ft}	=	disturbance terms, and
$\alpha's$, $\beta's$, $\theta's$ and ϕ_f	=	parameters to be estimated.

In this system of equations, the world CAPM implies the restriction that

$$\beta_{dv} = \beta_{dc} = \beta_{fv} = \beta_{fc} \ . \tag{11}$$

If the world CAPM holds, the constrained value of β's is an estimate of the aggregate relative risk aversion. The dynamics of the conditional covariance-variance matrix is specified to follow the bivariate GARCH of Engle and Kroner (1995). As CKS discuss, this specification allows for sufficient generality, while the number of parameters to be estimated is within a feasible range. In particular, this specification captures well the spillovers of volatility across national markets, studied by Hamao, Masulis, and Ng (1990), Lin, Engle, and Ito (1994), and Bae and Karolyi (1994). Furthermore, this specification guarantees that the covariance matrices are positive definite.

The conditional expected returns are allowed to depend on two lagged disturbances to incorporate the effect of infrequent trading on the index returns (Stoll and Whaley 1990b). CKS also allow the foreign returns to depend on the lagged disturbance of the domestic returns (U.S. market returns) through ϕ_f to take into account nonsynchronism in trading hours. Specifically, the U.S. market closes after most of foreign markets close on the same calendar day. Therefore, to the extent to which the contemporaneous returns on both markets are correlated, today's U.S. return can be used to improve the forecast of the next day's foreign return. This effect is relevant because CKS assume that investors form their expectations at the close of the U.S. market.

In this thesis, the econometric specification of the world CAPM follows that of CKS except that equations (9a) and (9b) are replaced as follows:

$$r_{dt} = \alpha_d + \beta_{dv}\omega_{dt-1}h_{dt} + \beta_{dc}(1-\omega_{dt-1})h_{ct} + \varepsilon_{dt} \,, \tag{12a}$$

$$r_{ft} = \alpha_f + \beta_{fv}\omega_{ft-1}h_{ft} + \beta_{fc}(1-\omega_{ft-1})h_{ct} + \varepsilon_{ft} \,, \tag{12b}$$

with: $\beta_{dv} = \beta_{dc} = \beta_{fv} = \beta_{fc}$,

$$\varepsilon_t \sim N(0,\, H_t) \text{ where } \varepsilon_t = (\varepsilon_{dt}, \varepsilon_{ft})' \text{ and } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix}, \tag{13a}$$

$$H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A. \tag{13b}$$

The system of equations (12a) and (12b) does not include the own lagged disturbance terms which are used to capture the effects of the nonsynchronous trading of component securities in the index in the CKS study. Since the technical trading rules tend to take advantage of positive autocorrelation in the index returns, there is the possibility that the models with own lagged disturbance terms could explain away the technical rule profits simply because of the specification having lagged disturbances. In other words, it would be mistakenly concluded that the equilibrium model could explain the technical rule profits even if the time-varying expected return implied by the equilibrium model did not play any major role. In order to avoid this problem, the system of equations (12a) and (12b) does not include own lagged disturbances; rather, the effects of the nonsynchronous trading on technical rule profits are considered by applying the standard test statistics to trading rule returns with a one-day lag.

System (12) also drops a cross-market disturbance term which is used to adjust for the nonsynchronous trading hours between the U.S. and foreign markets in the CKS study. The cross-market disturbance is included in the CKS study because they assume that investors form expectations at the close of the U.S. market. However, this thesis takes local investors' perspective and assumes that investors form their expectations at the close of the local market because trading rule signals are emitted at the close of the local market. Therefore, in a bivariate setting of the domestic market (which is not the U.S. market in this thesis) versus the foreign markets of which the major part is the U.S. market, the domestic (local) investors can not observe the U.S. or foreign market return at the close of the domestic market. Thus, a cross-market disturbance terms is not included in system (12).

The parameters of the model are estimated, using the maximum likelihood. Numerical maximization algorithm following Berndt, Hall, Hall and Hausman (1974) yields asymptotic standard errors and associated t statistics. This thesis also reports t statistics based on the standard errors that are robust to departure from normality suggested by Bollerslev and Wooldridge (1992). The world CAPM implies the restriction that $\beta_{dv} = \beta_{dc} = \beta_{fv} = \beta_{fc}$. This thesis provides some information on the validity of the world CAPM by conducting the likelihood ratio test for the restriction. The test statistic is distributed as χ^2 with the degree of freedom equal to three.

4.3 Mild segmentation

Assuming that the domestic market is mildly segmented in a two-country setting of the domestic versus foreign markets (assumption (A4)), returns on securities in the domestic market are determined both by the local and international risk premiums (Errunza and Losq 1985). This thesis uses the empirical model incorporating this implication as a benchmark model corresponding to mild segmentation. Some background relating the model of Errunza and Losq (1985) to the empirical model to be used in this thesis is discussed below.

Errunza and Losq (1985) show that if the domestic market is mildly segmented, the following relation holds unconditionally for the return on the domestic market:

$$E(r_d) = AMcov(r_d, r_m) + (A_d - A)M_d(1-\rho)var(r_d) \,, \tag{14}$$

with $A^{-1} \equiv (A_d^{-1} + A_f^{-1})$,

where: r_d = excess return on the domestic market portfolio,

r_m = excess return on the world market portfolio,

M = market value of the world market portfolio,

M_d = market value of the domestic market portfolio,

A_d = aggregate absolute risk aversion of domestic investors,

A_f = aggregate absolute risk aversion of foreign investors,

A = absolute risk aversion for the aggregate population, and

ρ = multiple correlation coefficient between r_d and the returns on securities in the foreign market.

By definition, r_m can be expressed as follows:

$$r_m = \frac{M_d}{M} r_d + \frac{M_f}{M} r_f , \tag{15}$$

where M_f is the market value of the foreign market portfolio (i.e., $M \equiv M_d + M_f$), and r_f is the excess return on the foreign market portfolio. Inserting equation (15) into equation (14), equation (14) can be re-written as:

$$E(r_d) = \lambda_d \omega_d var(r_d) + \lambda_f \omega_f cov(r_d, r_f) , \tag{16}$$

with: $\lambda_d = [A+(A_d-A)(1-\rho)]M$, and $\lambda_f = AM$,

where: ω_d = fraction of the domestic market relative to the world wealth, and
ω_f = fraction of the foreign market relative to the world wealth.

This thesis interprets λ_d and λ_f as the prices of domestic and foreign risks, respectively. The asset pricing relation expressed in equation (16) can be easily converted into its conditional form by replacing the unconditional operators of expectation (*E*), variance (*var*) and covariance (*cov*) with their conditional operators. It is assumed, for the empirical implementation of the model, that the prices of domestic and foreign risks are constant over time. Although this assumption certainly makes this thesis depart from the theoretical model of Errunza and Losq (1985), this thesis focuses on their model's intuition that the expected return on the mildly segmented market contains both domestic and international risk premiums.

The econometric specification for the model is given as follows:

$$r_{dt} = \alpha_d + \beta_{dv}\omega_{dt-1}h_{dt} + \beta_{dc}(1-\omega_{dt-1})h_{ct} + \varepsilon_{dt} , \tag{17a}$$

$$r_{ft} = \alpha_f + \beta_{fv}\omega_{ft-1}h_{ft} + \beta_{fc}(1-\omega_{ft-1})h_{ct} + \varepsilon_{ft} , \tag{17b}$$

with: $\beta_{fv} = \beta_{fc}$,

$$\varepsilon_t \sim N(0,\ H_t) \text{ where } \varepsilon_t = (\varepsilon_{dt}, \varepsilon_{ft})' \text{ and } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix}, \tag{18a}$$

$$H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A \ , \tag{18b}$$

where:

r_{dt}	=	return on the domestic market portfolio in the excess of the riskless rate,
r_{ft}	=	return on the foreign market portfolio in the excess of the riskless rate,
h_{dt}	=	conditional variance of the domestic market portfolio,
h_{ft}	=	conditional variance of the foreign market portfolio,
h_{ct}	=	conditional covariance of the domestic market portfolio with the foreign market portfolio,
ω_{dt}	=	fraction of the domestic market portfolio relative to the world wealth,
ω_{ft}	=	fraction of the foreign market portfolio relative to the world wealth,
H_t	=	2×2 conditional covariance matrix,
C	=	2×2 upper triangular matrix of parameters to be estimated,
A and G	=	2×2 matrices of parameters to be estimated,
ε_{dt} and ε_{ft}	=	disturbance terms, and
$\alpha's$ and $\beta's$	=	parameters to be estimated.

Two parameters, β_{dv} and β_{dc}, corresponding to the prices of domestic and foreign risks are freely estimated under this specification. The dynamics of the conditional covariance-variance matrix is specified to follow the bivariate GARCH of Engle and Kroner (1995). The parameters of the model are estimated, using the maximum likelihood estimation. This thesis reports both standard t statistics and alternative t statistics robust to departure from normality suggested by Bollerslev and Wooldridge (1992).

The restriction that $\beta_{fv} = \beta_{fc}$ assumes that the foreign market is internally integrated and that the world CAPM relation holds for the foreign market, as Errunza and Losq (1985) assume. Certainly, the foreign market might have more complicated structure than they are integrated. For example, the foreign market might consist of many mutually integrated markets and a few segmented markets. However, aggregating pricing implications from such complicated market structure is a difficult task and beyond the scope of this thesis. Nonetheless, this thesis provides some information on the validity of this assumption by reporting the likelihood-ratio-test statistic for the restriction $\beta_{fv} = \beta_{fc}$. The test statistic is distributed as χ^2 with the degree of freedom equal to one.

4.4 Complete segmentation

Under the complete segmentation (assumption (A5)), there is no capital flow between the domestic and foreign markets. Therefore, the expected returns on securities in both markets are determined independently. For the domestic market, the conditional version of the purely domestic CAPM holds. Assuming the constant aggregate relative risk aversion, the following relation holds for the expected return on the domestic market portfolio:

$$E(r_{dt}|\Omega_{t-1}) = \lambda_t var(r_{dt}|\Omega_{t-1}) \ , \tag{19}$$

where: r_{dt} = excess return on the domestic market portfolio,

Ω_{t-1} = information set available to investors at t-1, and

λ_t = the aggregate relative risk aversion of domestic investors.

The econometric specification of the domestic CAPM uses a bivariate setting of the domestic versus foreign markets. The assumption that both domestic and foreign markets are segmented from each other does not imply both markets are uncorrelated. It is assumed again that the foreign market is internally integrated. Thus, securities in the foreign market are priced according to the conditional CAPM with the foreign market portfolio being a factor. If the domestic (foreign) market is segmented, the covariance with the foreign (domestic) market should not be priced. This notion is used to verify the validity of the model. The empirical model corresponding to the complete integration is given as:

$$r_{dt} = \alpha_d + \beta_{dv} h_{dt} + \beta_{dc} h_{ct} + \varepsilon_{dt} , \tag{20a}$$

$$r_{ft} = \alpha_f + \beta_{fv} h_{ft} + \beta_{fc} h_{ct} + \varepsilon_{ft} , \tag{20b}$$

$$\text{with: } \beta_{dc} = \beta_{fc} = 0,$$

$$\varepsilon_t \sim N(0, \boldsymbol{H}_t) \text{ where } \varepsilon_t = (\varepsilon_{dt}, \varepsilon_{ft})' \text{ and } \boldsymbol{H}_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix}, \tag{21a}$$

$$\boldsymbol{H}_t = \boldsymbol{C}'\boldsymbol{C} + \boldsymbol{G}'\boldsymbol{H}_{t-1}\boldsymbol{G} + \boldsymbol{A}'\varepsilon_{t-1}\varepsilon_{t-1}'\boldsymbol{A} , \tag{21b}$$

where:

r_{dt}	=	excess return on the domestic market portfolio,
r_{ft}	=	excess return on the foreign market portfolio,
h_{dt}	=	conditional variance of the domestic market portfolio,
h_{ft}	=	conditional variance of the foreign market portfolio,
h_{ct}	=	conditional covariance of the domestic market portfolio with the

foreign market portfolio,

H_t = 2×2 conditional covariance matrix,

C = 2×2 upper triangular matrix of parameters to be estimated,

A and G = 2×2 matrices of parameters to be estimated,

ε_{dt} and ε_{ft} = disturbance terms, and

$\alpha's$ and $\beta's$ = parameters to be estimated.

The asset pricing relations for both domestic and foreign markets are expressed without market value weights. The dynamics of the conditional covariance-variance matrix is specified to follow the bivariate GARCH of Engle and Kroner (1995). The parameters of the model are estimated, using the maximum likelihood. Both standard t statistics and alternative t statistics robust to departure from normality suggested by Bollerslev and Wooldridge (1992) are reported. This thesis provides some information on the validity of the model by computing the likelihood-ratio-test statistic for the restriction $\beta_{dc} = \beta_{fc} = 0$. The test statistic is distributed as χ^2 with the degree of freedom equal to two.

Chapter 5 Bootstrap Tests

The standard tests of trading rules which are explained in Chapter 3 compare the conditional mean returns on the trading rule strategy with the unconditional mean return on the index which is equivalent to the mean return on the buy-and-hold strategy. However, if the risk of the buy and hold is different from that of the trading rules and if expected returns vary over time, the use of the unconditional mean return as a benchmark could be inappropriate. Instead, employing the bootstrap methodologies with equilibrium asset pricing models for time-varying expected returns, this thesis constructs the empirical distributions of the trading rule returns which can be considered to reflect the risk-return relation implied by the equilibrium models. The trading rules are evaluated by comparing the empirical distribution of trading rule profits with the actual profits.

As Efron (1979) and BLL (1992) point out, there are several benefits from using the bootstrap methodologies in examining the trading rules. First, the bootstrap methodologies make it possible to conduct a joint test across the different trading rules which are dependent on each other in a complex manner. Traditional tests statistics are difficult to apply when such complex dependencies exist among the trading rules. Second, standard test statistics frequently assume independent, stationary and asymptotically normal distributions. However, daily returns are likely to exhibit several deviations from the assumptions, such as autocorrelation, conditional heteroscedasticity, skewness and excess kurtosis. The bootstrap methodologies can take into account such deviations by using empirical error distributions obtained from a null model that incorporates some of the deviations.

5.1 Hypotheses

In this thesis, three different types of conditional asset pricing models corresponding to complete integration, mild segmentation and complete segmentation are used for the bootstrap tests. In testing trading rule profits with these conditional asset pricing models, at least the following hypotheses are implicitly added: equity markets of interest are efficient; the conditional mean-variance framework is correct; and returns are measured with reasonably small errors.[5] In other words, all null hypotheses have a joint-hypothesis nature typical in the empirical literature of finance (Fama 1991). In order to clarify the focus of this thesis, however, null hypotheses to be tested are summarized as follows:

Hypothesis 1:

Trading rule profits are consistent with the complete integration.

(Alternative hypothesis: not consistent with the complete integration.)

Hypothesis 2:

Trading rule profits are consistent with the mild segmentation.

(Alternative hypothesis: not consistent with the mild segmentation.)

Hypothesis 3:

Trading rule profits are consistent with the complete integration.

(Alternative hypothesis: not consistent with the complete integration.)

A rejection of a particular hypothesis indicates that a given null model relating to the hypothesis can not explain away the trading rule profits. A failure to reject any of the three hypotheses indicates that the trading rule profits are consistent with the risk-return relation implied by the null model of an unrejected hypothesis. If all null hypotheses are rejected, the joint-hypothesis problem arises (Fama 1991). That is, the rejection of the null hypotheses may be due to market inefficiency, inappropriate framework for asset pricing models,

---

[5] Major causes of measurement errors in daily returns, which are pointed out in the literature, include nonsynchronous trading (Stoll and Whaley 1990b) and bid-ask bounce (Roll 1984).

measurement errors in returns, or any combination among them. In addition to the three equilibrium models, the random walk with a drift is used for the bootstrap tests in order to examine whether allowing for time-variation of expected returns makes any difference, compared to the model with the constant expected return, which is implied by the random walk with a drift.

5.2 Bootstrap methodologies

This thesis follows the parametric bootstrap methodologies of Freedman and Peters (1984), BLL (1992), Kho (1996), and Karolyi and Kho (1996). The theoretical distribution of an unobservable error term is approximated by the empirical distribution of observable residuals. First, a null model is estimated by using the actual return series to obtain estimated parameters and residuals. Probability mass 1/N is put on each residual to approximate the theoretical distribution, where N is the number of observations. Residuals are drawn with replacement at the assigned probability to form a scrambled residual series which is then used with the estimated parameters to generate a new representative return series for the given null model. The simulated returns are exponentiated back to a simulated price series with an initial value for the price in the sample. The trading rules are applied to the simulated series, and the empirical distributions of the trading rule returns are obtained by repeating this procedure 500 times. The fraction of the 500 replications, which generates a value greater than that from the actual series, is interpreted as a simulated p-value.

This thesis posits as a null model various forms of equilibrium asset pricing models. Therefore, if the simulated distributions can reproduce the actual profits reasonably well, such results imply that the actual profits are consistent with the risk-return relation implied by the equilibrium models. The profit measures for which the empirical distributions are constructed include the mean return conditional on buy signals, the mean return conditional on sell signals, and the difference between the conditional mean buy and sell returns (buy-sell spread). The null hypothesis is rejected at the α precent significance level if the returns obtained from the actual series fall in the α precent critical region of the simulated distributions under the null model. In the bootstrap simulations, what is an appropriate level for α is not clear. Although this thesis follows conventional cut-off levels, all simulated p-values are reported in subsequent tables so that readers can judge significance of results by themselves.

For the random walk with a drift, the actual return series are randomly drawn with replacement to form a new return series. The three equilibrium models are bivariate GARCH models; following Kho (1996) and BLL, this thesis standardizes a vector of estimated residuals by $\hat{z}_t = \hat{H}_t^{-1/2}\hat{\varepsilon}_t$, where $\hat{\varepsilon}_t$ is a vector of residuals, $\hat{H}_t^{-1/2}$ is the inverse of the Cheloskey factor of the estimated variance-covariance matrix and $\hat{z}_t$ is a vector of the resulting standardized residuals. With initial values for the elements of $\hat{H}_1$, the standardized residuals are drawn with replacement, and unobservable errors are obtained recursively by $\hat{\varepsilon}_t^* = \hat{H}_t^{1/2*}\hat{z}_t^*$, where * denotes simulated values.

The world CAPM and the asset pricing model under the mild segmentation use the weights of domestic and foreign market values. It is assumed that the market values move together with the equity market index level. Thus, for each simulation, the market values of both markets are computed by using the simulated returns and the initial market values in the sample.

Chapter 6 Data

6.1 Selection of countries

The countries to which this thesis applies the technical trading rules include Japan, U.S. and Canada from among developed markets and Indonesia, Mexico and Taiwan from among emerging markets. Developed markets do not impose any severe restrictions on capital flow and can be expected to be more integrated with the world than segmented. In contrast, according to a widely accepted view, emerging markets are more likely to be segmented from the rest of the world than developed markets due to the governments' restrictions on capital flow. The examinations of both advanced and emerging markets may increase the ex-ante probability of obtaining results consistent with the existence of different international market structures. Motivations for selecting the individual countries and some background about the markets are briefly explained below.

(a) Japan

Japan is included because the Japanese equity market is the second largest in the world at the time of this thesis. While Harvey's (1991) results indicate that Japan is not fully integrated with the rest of the world, evidence for the integration of Japan has been provided by Gultekin, Gultekin and Penati (1989), CKS (1992) and Ferson and Harvey (1993). Bessembinder and Chan (1995) apply the technical trading rules to data on the Japanese equity market index and find weak evidence for the forecast power of the technical rules. Although these studies use data prior to 1990, this thesis includes a more recent sample during the 1990's corresponding to the post-"bubble" period.

(b) U.S.

BLL (1992) have found that simple technical trading rules can predict future returns on the Dow Jones Index by using data over the ninety-year period. Since their data end in 1986, it will be of interest to examine whether the trading rules continue to hold forecast power for the recent sample.

(c) Canada

Whether Canada is integrated with other markets, particularly the U.S., has been a controversial issue. While Jorion and Schwarts (1986), Foerster and Karolyi (1993), and Karolyi (1995) provide evidence that Canada is segmented relative to the U.S. market, Mittoo (1992), Errunza, Losq, and Padmanabhan (1992) and Alexander, Eun, and Janakiramanan (1988) provide evidence for the integration with the U.S. market. This thesis will contribute to this debate by providing additional evidence.

(d) Indonesia

The Indonesian equity market is relatively new to academics and practitioners. Roll (1995) conducts an empirical survey of this new market and reports evidence of imperfect adjustment to new information for some individual stocks in the market. Such imperfect adjustment may provide a profitable opportunity for the use of the technical trading rules. In the 1980's, the government's various restrictions including control on the operations of exchanges and limits on foreign ownership prevented the development of the stock markets. However, foreign portfolio demand for Indonesian stocks serged in 1989-1990; subsequently, the government started to let the stock markets develop by relaxing their direct controls. The number of companies listed increased from only 24 in 1988 to 216 at the end of 1994 (Cole and Slade 1996). The foreign ownership restriction up to 49% was still effective in 1994.

(e) Mexico

Mexico is included in a North American context because the Mexican equity market historically received much attention from U.S. investors. The liberalization of the Mexican equity market is relatively recent. Restrictions of foreign investments were abolished in 1989. Thus, Mexican stocks were made 100 percent investable. Subsequently, the dual exchange rate system was unified in 1991. Bekaert and Harvey (1995) provide evidence that Mexico is more segmented than integrated in most of the 1980's and early 1990's.

(f) Taiwan

Taiwan is one of the most growing emerging markets. However, it is also known as one of the most restrictive emerging markets. In 1991, foreign institutional investors who met certain highly restrictive requirements were allowed to invest in the market directly. In 1993, the maximum foreign securities holdings limit was further increased. Bakaert and Harvey (1995) provide evidence for the global integration of Taiwan in most of 1985-1992. Bessembinder and Chan (1995) report the large profits on the technical trading rules for Taiwan during 1975-1989. This thesis examines trading rule returns and the issue of integration and segmentation for Taiwan, using more recent data.

6.2 Description of data

Data on daily closing level of national equity market indices are obtained from Datastream International. The Datastream indices consist of a representative sample of stocks covering a wide variety of industry sectors in each country. The suitability of inclusion of individual stocks is primarily determined by market value and availability of data; the largest value stocks for each country, which cover at least 75 to 80 percent of the total market value, are included. The liquidity of individual stocks is not explicitly taken into account as an inclusion criterion. Thus, the Datastream indices could include more stocks with relatively low liquidity than the indices the constituents of which concentrate on large, highly liquid stocks, such as the S&P 500 index in the U.S. However, an inclusion of illiquid stocks may not be very serious because the capitalization size is often related to liquidity of individual stocks (Stoll and Whaley 1983). The number of stocks for each index varies, depending on the size of the market. The approximate numbers of stocks included in 1996 are 1000 for the Japan index, 1000 for the U.S. index, 250 for the Canada index, 50 for the Indonesia index, 90 for the Mexico index, and 70 for the Taiwan index.

Datastream indices exclude the following securities: fixed interest stocks, unit trusts, mutual funds, investment funds, warrants, foreign listings including American Depositary Receipts (ADRs), and foreign board stocks. There is no special account for cross-holdings of stocks, typically observed in Japan (French and Poterba 1991). The Datastream indices are adjusted to dividends.

The period of available data varies, depending on the country. For the developed markets, the period of sample is from January 1, 1980 to December 31, 1996. The starting year of 1980 was selected because international capital flows among developed markets became evident in the 1980's. For the emerging markets, the period of the sample is relatively short due to limited availability of data; April 2, 1990 - December 31, 1996 for the Indonesia index, January 4, 1988 - December 31, 1996 for the Mexico index, and January 26, 1988 - December 31, 1996 for the Taiwan index. As discussed earlier, however, the development and liberalization of the emerging markets to be examined started in the late 1980's. Therefore, the sample in these periods may not be contaminated seriously by the structural changes due to regime shifts. For the U.S., the Dow Jones index (DJIA) is also examined because BLL use this index. All these indices are denominated by a local currency. Daily returns on the national equity market index are calculated as differences of the logarithms of closing prices.

In order to estimate a GARCH model under the bivariate setting of the domestic and foreign markets, it is necessary to obtain the returns on the foreign market for each of the countries to be examined as a domestic market. For each country, the returns on the Datastream world index converted into the currency of the country are used with a market value for the country to compute the returns on the foreign market. The Datastream world index is a value-weighted equity market index with dividends, consisting of a wide variety of countries including advanced and emerging markets as of 1994. Foreign market returns corresponding to each of the countries to be examined as a domestic market are continuously compounded and are denominated by a currency of the country defined as a domestic market. Data on market values for individual countries and world index were also available from Datastream International.

In addition to the national equity market indices, this thesis uses data on daily closing prices of the Nikkei index futures contracts traded on the Chicago Mercantile Exchange (CME) as a proxy for the Japanese equity market. There are several motivations for the use of the Nikkei index futures contracts. First, Craig, Dravid and Richardson (1995) find that the Nikkei index futures traded in the U.S. provide complete information about the contemporaneous overnight returns on the Nikkei index traded in Japan. The Nikkei index is based on the arithmetic average of stock prices across 225 large firms and have been a popular measure for the market-wide performance. Second, futures contracts are not subject to problems related to the nonsynchronous trading of component securities in the index. Third, in this thesis's context, problems due to nonsynchronous trading hours across countries can be avoided if the U.S.-traded Nikkei index futures are used with the S&P 500 index, another U.S.-traded index, being a proxy for the foreign market. Finally, the effects of transaction costs are minimal for futures contracts.

The Nikkei index futures were introduced in the CME in September 1990. Delivery months for the Nikkei index futures are March, June, September and December. Successive daily closing prices from a contract closest to expiration are used, with the exception of the last day of trading; on this day, the next-maturity contract is used. The period of the sample for the Nikkei index futures is December 14, 1990 - December 12, 1996. Data on the first three month were excluded to avoid an instable start-up period. Although the prices of the Nikkei index futures contracts are denominated by U.S. dollars, the level of the futures contract price is considered to be a proxy for yen-value of the Nikkei index traded in Japan (Hull 1993).[6] Therefore, the S&P 500 index, which is used as a proxy for the foreign market, is converted into yen by using the exchange rate prevailing at the close of the U.S. market. Daily returns on the Nikkei index futures and the S&P 500 index are calculated as differences of the logarithms of closing prices. Data on the Nikkei index futures, S&P 500 index, and exchange rates are obtained from Datastream International.

The excess return is defined as the raw return on a portfolio minus the local interest rate in a country of the currency which denominates the portfolio return: the Japanese interbank call rates are used for yen-denominated excess returns; the three-month U.S. Treasury bill rates for U.S.-dollar-denominated excess returns; the one-month Canadian Treasury bill rates for Canadian-dollar-denominated excess returns; the Indonesian interbank call rates for rupiah-denominated excess returns; the Taiwanese interbank swap overnight rates for Taiwan-dollar-denominated excess returns. For Mexico-peso-denominated returns, only monthly data on the one-month Treasury bill yields from International Financial Statistics are available. Therefore, the monthly Treasury bill yields are used, assuming that the yields do not change over a month.[7] Data on the Japanese interbank call rate were obtained from Nikkei Inc; data on the U.S. Treasury bill rates were from Citibank. Data on the other interest rates were obtained from Datastream International.

---

[6] Studies on the stock index arbitrage (Stoll and Whaley 1987, 1990b; Brenner, Subrahmanyam, and Uno 1990; Lim 1990; Miller, Muthuswamy, and Whaley 1994; Karolyi 1996) examine deviation of the index futures contract from the underlying stock index. Whether the Nikkei index futures contract is a proxy for the Japanese equity market will be discussed later by relating the issue to the empirical results in this thesis.

[7] French, Schwert, and Stambaugh (1987) calculate daily excess returns using data on daily equity index returns and monthly yields of treasury-bill bonds under the same assumption as this thesis.

Chapter 7 Results and Analysis

7.1 Summary statistics

Summary statistics for daily national and foreign equity market returns are reported in Table 1 for the developed markets and Table 2 for the emerging markets.

The Datastream equity market indices are used to compute the national equity market returns. For each country, the foreign market returns (denoted by Non-Japan, Non-U.S., Non-Canada, Non-Indonesia, Non-Mexico and Non-Taiwan) are calculated using returns on the Datastream world index converted into the currency of the country and market values for the country. In addition, the Nikkei index futures and Dow Jones index are included as proxies for the Japanese and U.S. equity market, respectively. Returns on the S&P 500 index converted into yen are used as a proxy for the foreign market corresponding to the Nikkei index futures. All returns are continuously compounded. The periods of the sample vary, depending on the country. The periods of the sample for the developed markets cover January 1980- December 1996, except for the Nikkei index futures; the periods of the sample for the emerging markets are relatively short, covering the periods after the worldwide market crash which occurred in October 1987. For the developed markets, statistics corresponding to two subperiods without October 1987, the month of worldwide market crash, are reported.

Panel A in Table 1 and 2 shows several distributional statistics. The sample for Japan includes the period during which the Japanese equity market performed poorly; the mean return on the Datastream Japan index for the second subperiod and the mean return on the Nikkei index futures are both negative. The three emerging markets exhibit high volatility, compared with the developed markets. In particular, the standard deviation of Taiwan is almost three times as large as that of the Datastream U.S. index for the second subperiod.

Table 1

Summary statistics for daily national equity market returns and foreign market returns for developed markets (Japan, U.S. and Canada)[a]

Statistics	Japan vs Foreign				U.S. vs Foreign			Canada vs Foreign	
	Japan (Yen)	Nikkei Futures (Yen)	Non-Japan (Yen)	S&P (Yen)	U.S. (US$)	Dow Jones (US$)	Non-U.S. (US$)	Canada (C$)	Non-Canada (C$)
Panel A: Distributional statistics									
Period	80.1-96.12	90.12-96.12	80.1-96.12	90.12-96.12	80.1-96.12	80.1-96.12	80.1-96.12	80.1-96.12	80.1-96.12
Nobs.	4435	1564	4435	1564	4435	4435	4435	4435	4435
Mean (%)									
Overall period	0.0315	-0.0266	0.0364	0.0410	0.0578	0.0460	0.0478	0.0400	0.0553
80.1-87.9	0.0859	-	0.0420	-	0.0710	0.0559	0.0823	0.0529	0.0853
87.11-96.12	-0.0091	-	0.0449	-	0.0571	0.0491	0.0251	0.0401	0.0374
Std. Dev. (%)									
Overall period	1.0096	1.4272	0.8841	0.9590	0.8932	0.9938	0.8586	0.7466	0.7224
80.1-87.9	0.7549	-	0.8607	-	0.8583	0.9188	0.8259	0.8183	0.6748
87.11-96.12	1.1122	-	0.8092	-	0.7588	0.8429	0.8066	0.5514	0.6895
Skewness	-0.5261*	0.1859*	-1.4010*	-0.3964*	-2.8969*	-3.9279*	-1.1084*	-1.1846*	-0.5974*
Kurtosis	24.306*	5.151*	24.498*	5.752*	69.705*	108.724*	24.793*	32.315*	15.879*
Kolmogorov D	0.0923*	0.0658*	0.0575*	0.0491*	0.0785*	0.0742*	0.0528*	0.0841*	0.0478*
Panel B: Autocorrelations Series: R_t									
ρ_1	0.1114*	-0.0744*	0.1278*	-0.0292	0.0857*	0.0245	0.1124*	0.1741*	0.1661*
ρ_2	-0.0470*	-0.0032	-0.0092	0.0078	-0.0221	-0.0365	0.0156	0.0304	0.0033
ρ_3	0.0060	0.0188	-0.0095	-0.0383	-0.0259	-0.0185	0.0157	0.0185	-0.0026
Series: R^2_t									
ρ_1	0.2629*	0.1414*	0.0548*	0.0286	0.0900*	0.0888*	0.2539*	0.4063*	0.4964*
ρ_2	0.0748*	0.1140*	0.1912*	0.0174	0.1708*	0.1448*	0.0348*	0.3421*	0.2928*
ρ_3	0.1081*	0.1078*	0.1250*	0.0313	0.0923*	0.0655*	0.0583*	0.2230*	0.1727*

[a] * Signicant at the 1 % level.

Table 2
Summary statistics for daily national equity market returns and foreign market returns for emerging markets (Indonesia, Mexico and Taiwan)[a]

Statistics	Indonesia vs Foreign		Mexico vs Foreign		Taiwan vs Foreign	
	Indonesia (RI)	Non-Indonesia (RI)	Mexico (MP)	Non-Mexico (MP)	Taiwan (T$)	Non-Taiwan (T$)
Panel A: Distributional statistics						
Period	90.4-96.12	90.4-96.12	88.1-96.12	88.1-96.12	88.1-96.12	88.1-96.12
Nobs.	1761	1761	2346	2346	2330	2330
Mean (%)	0.0047	0.0511	0.1418	0.0898	0.0312	0.0343
Std. Dev. (%)	1.1334	0.8509	1.4306	1.3056	2.2015	0.7917
Skewness	-0.0360•	-0.1345•	0.3125•	2.0650•	-0.0144•	-0.2512•
Kurtosis	10.458•	7.8635•	12.336•	54.312•	5.524•	7.502•
Kolmogorov D	0.1041•	0.0725•	0.0791•	0.1462•	0.0863•	0.0619•
Panel B: Autocorrelations Series: R_t						
ρ_1	0.2513•	-0.0793•	0.2880•	-0.0796•	0.0543•	-0.0282
ρ_2	0.0881•	-0.0272	0.0252	-0.0375	0.0507	-0.0160
ρ_3	0.0141	-0.0307	0.0490	0.0381	0.0360	-0.0161
Series: R^2_t						
ρ_1	0.3604•	0.1284•	0.3292•	0.1607•	0.1840•	0.0819•
ρ_2	0.3186•	0.0706•	0.1550•	0.1975•	0.3238•	0.1294•
ρ_3	0.0609•	0.1085•	0.1202•	0.3455•	0.2383•	0.1091•

[a] RI denotes rupiah, MP Mexican pesos, and T$ Taiwan dollars. • Signicant at the 1 % level.

Table 3
Summary statistics for market capitalization (percent)

Statistics	Japan	U.S.	Canada	Indonesia	Mexico	Taiwan
Overall period:	80.1-96.12	80.1-96.12	80.1-96.12	90.4-96.12	88.1-96.12	88.1-96.12
Mean	28.788	40.242	2.541	0.209	0.523	1.157
Std. dev.	8.303	9.143	0.481	0.111	0.366	0.426
Min.	17.227	25.714	1.906	0.085	0.031	0.354
Median	25.892	37.687	2.287	0.141	0.512	1.063
Max.	48.413	57.692	3.839	0.444	1.345	2.636
Subperiod: 80.1-87.9						
Mean	24.372	48.685	2.964			
Std. dev.	5.867	5.939	0.410			
Min.	17.227	31.333	2.070			
Median	22.828	49.960	3.122			
Max.	42.479	57.692	3.839			
Subperiod: 87.11-96.12						
Mean	32.406	33.189	2.187			
Std. dev.	8.232	3.804	0.097			
Min.	18.013	25.714	1.906			
Median	30.318	33.288	2.175			
Max.	48.413	40.390	2.459			

The high mean return for Mexico reflects a high inflation rate in this country. All return series exhibit the skewness and kurtosis which are significantly different from those of a normal distribution. Kolmogorov D statistics further confirm statistically significant departure from normality for all return series.

The autocorrelations of raw and squared returns are shown in Panel B in Table 1 and 2. In general, significant autocorrelations with the order of one or two are exhibited for raw returns, except for the S&P 500 index, Dow Jones index, and Non-Taiwan. The significant positive and declining autocorrelations for the squared returns are also observed, except for the S&P 500 index. The GARCH model that this thesis estimates later can capture this type of nonlinear dependence.

Table 3 reports summary statistics for market capitalization as faction of the total market value of the Datastream world index. The market values of U.S. and Japan are far larger than the other countries. The combined value of both countries averages about 69 percent during January 1980 - December 1996, and about 66 percent for the second subperiod during which many emerging markets developed rapidly. The market values of the emerging markets are small, less than two percent of the total market value of the Datastream world index.

7.2 Profits on the technical trading rules and standard test results

Standard test statistics are applied to the three different groups of technical trading rules; variable-length moving average (VMA) rules, fixed-length moving average (FMA) rules and trading range break (TRB) rules for various country-based indices. The effects of transaction costs on the trading rule returns are also examined.

The results are shown in Table 4 to 11. The format of presentation is the same across the tables. Panel A, B and C report results about the VMA, FMA and TRB rules, respectively.

The column labelled Buy (Sell) under Nobs. reports the number of the days which generate buy (sell) signals. Similarly, the column labelled Buy (Sell) under Std. dev. (%) reports the standard deviation of daily returns in percent conditional on buy (sell) signals. The column labelled Buy (Sell) under Mean return (%) reports the mean daily return in percent conditional on buy (sell) signals. The column labelled Buy-Sell under Mean return (%) reports the difference between the mean buy and sell returns, i.e., the mean return conditional on buy signals minus the mean return conditional on sell signals. This thesis refers to this statistic as the buy-sell spread. T-statistics corresponding to individual rules test the difference between the mean buy and unconditional mean returns, the difference between the mean sell and unconditional mean returns, and the difference between the mean buy and sell returns (the buy-sell spread). These t statistics are obtained from the Cumby-Modest (1987) regression tests and are based on the heteroscedasticity-consistent standard errors (White 1980). The columns labelled Buy, Sell, and Buy-Sell under t statistic in the tables report the t statistics. Adj. R^2 in the last column is for the regressions of the equity index returns on both buy and sell signals. The rows labelled χ^2:(p−value) report p-values for the Wald test statistics testing the hypothesis that the conditional mean returns are equal to the unconditional mean returns across individual rules.

For the overall period, the returns on individual rules as well as the averages across individual rules for each of the VMA, FMA and TRB rules are reported. In addition, for the overall period, the averages across individual rules for trades with a 1-day lag are reported in order to adjust for nonsynchronous trading. For two subperiods without the month of the market crash, October 1987, the average returns across individual rules executed with a 0-day lag are reported for each of the VMA, FMA, and TRB rules. For the VMA and FMA rules, individual rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percent difference that is needed to generate a signal. For the TRB rules, individual rules are identified as (window, band) where window is the length of prior period in recording recent minimum and maximum prices, and band is the percent difference that is needed to generate a signal. The results for each country

Table 4

Test results for the technical trading rules applied to the Datastream Japanese equity market index (1980.1-1996.12)[a]

	Trading rule	Nobs. Buy	Nobs. Sell	Std. dev. (%) Buy	Std. dev. (%) Sell	Mean return (%) Buy	Mean return (%) Sell	Mean return (%) Buy-Sell	t statistic Buy	t statistic Sell	t statistic Buy-Sell	Adj. R^2
Panel A: Results for VMA rules												
Returns with a 0-day lag	(1, 50, 0)	2557	1678	0.8464	1.2555	0.0763	-0.0383	0.1146	3.2835 ***	-3.2835 ***	3.2835 ***	0.0027
	(1, 50, 0.01)	2155	1302	0.7984	1.3627	0.1020	-0.0648	0.1668	4.5541 ***	-3.3868 ***	4.1920 ***	0.0050
	(1, 150, 0)	2785	1450	0.8190	1.3432	0.0586	-0.0224	0.0810	2.1024 **	-2.1024 **	2.1024 **	0.0012
	(1, 150, 0.01)	2614	1285	0.8232	1.3846	0.0626	-0.0227	0.0853	2.3030 **	-1.8532 *	2.1219 **	0.0012
	(5, 150, 0)	2787	1448	0.8271	1.3348	0.0532	-0.0119	0.0651	1.6948 *	-1.6948 *	1.6948 *	0.0007
	(5, 150, 0.01)	2608	1272	0.8310	1.3638	0.0589	-0.0302	0.0891	2.0382 **	-2.1175 **	2.1394 **	0.0012
	(1, 200, 0)	2890	1345	0.8254	1.3678	0.0541	-0.0190	0.0732	1.8153 *	-1.8153 *	1.8153 *	0.0009
	(1, 200, 0.01)	2745	1221	0.8312	1.3965	0.0573	-0.0211	0.0785	1.9961 **	-1.7106 *	1.8869 *	0.0010
	(2, 200, 0)	2887	1348	0.8255	1.3671	0.0509	-0.0119	0.0628	1.5592	-1.5592	1.5592	0.0006
	(2, 200, 0.01)	2744	1227	0.8275	1.3963	0.0556	-0.0245	0.0801	1.8608 *	-1.8288 *	1.8805 *	0.0010
	Average	2677.2	1357.6	0.8255	1.3572	0.0630	-0.0267	0.0896				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Returns with a 1-day lag	Average	2677.2	1356.6	0.8492	1.3385	0.0599	-0.0226	0.0825				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Subperiod 80.1-87.9	Average	1499.8	238.3	0.7636	0.8834	0.0966	0.0691	0.0276				
	χ^2_{10}:(p-value)					0.332	0.361	0.294				
Subperiod 87.11-96.12	Average	1045.2	1033.5	0.7939	1.3977	0.0273	-0.0580	0.0853				
	χ^2_{10}:(p-value)					<0.001	0.002	<0.001				
Panel B: Results for FMA rules												
Returns with a 0-day lag	(1, 50, 0)	2540	1695	0.8831	1.2156	0.0586	-0.0105	0.0691	2.0126 **	-2.0126 **	2.0126 **	0.0008
	(1, 50, 0.01)	2360	1572	0.8959	1.2519	0.0735	-0.0242	0.0977	2.9363 ***	-2.4477 **	2.7241 ***	0.0018
	(1, 150, 0)	2780	1455	0.8629	1.2881	0.0588	-0.0224	0.0812	2.1641 **	-2.1641 **	2.1641 **	0.0012
	(1, 150, 0.01)	2730	1373	0.8598	1.3217	0.0566	-0.0196	0.0763	1.9650 **	-1.9145 *	1.9524 *	0.0009
	(5, 150, 0)	2780	1455	0.8682	1.2817	0.0555	-0.0161	0.0716	1.9154 *	-1.9154 *	1.9154 *	0.0009
	(5, 150, 0.01)	2720	1351	0.8651	1.3227	0.0595	-0.0268	0.0862	2.1802 **	-2.1524 **	2.1842 **	0.0013
	(1, 200, 0)	2910	1325	0.8598	1.3279	0.0485	-0.0077	0.0562	1.4132	-1.4132	1.4132	0.0004
	(1, 200, 0.01)	2850	1291	0.8643	1.3331	0.0512	-0.0139	0.0651	1.6062	-1.5985	1.6121	0.0006
	(2, 200, 0)	2890	1345	0.8608	1.3207	0.0494	-0.0088	0.0582	1.4766	-1.4766	1.4766	0.0005
	(2, 200, 0.01)	2840	1290	0.8631	1.3357	0.0521	-0.0160	0.0681	1.6747 *	-1.6696 *	1.6833 *	0.0007
	Average	2740.0	1415.2	0.8683	1.2999	0.0564	-0.0166	0.0730				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Returns with a 1-day lag	Average	2740.0	1414.2	0.8704	1.2981	0.0557	-0.0163	0.0720				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Subperiod 80.1-87.9	Average	1527.1	253.0	0.7798	0.7989	0.0939	0.0797	0.0141				
	χ^2_{10}:(p-value)					0.864	0.911	0.879				
Subperiod 87.11-96.12	Average	1088.0	1066.2	0.8014	1.3795	0.0131	-0.0432	0.0563				
	χ^2_{10}:(p-value)					0.061	0.220	0.120				

Table 4 (continued)

Panel C: Results for TRB rules												
	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Returns with a 0-day lag	(50, 0)	1350	579	0.9161	1.5447	0.0983	-0.0192	0.1175	3.0951 [illegible]	-0.8798	2.2890 [illegible]	0.0016
	(50, 0.01)	510	435	0.8977	1.7798	0.1516	0.0546	0.0970	3.1730 ***	0.3060	1.1990	0.0004
	(150, 0)	1000	275	0.7318	2.0247	0.1095	-0.0209	0.1304	3.4072 ***	-0.4516	2.0805 **	0.0014
	(150, 0.01)	360	235	0.8929	2.1140	0.1660	0.0235	0.1425	2.9604 ***	-0.0564	1.3544	0.0007
	(200, 0)	950	220	0.7265	1.9203	0.1263	-0.0760	0.2023	4.0469 ***	-0.8670	2.9017 ***	0.0025
	(200, 0.01)	360	188	0.8904	2.0032	0.1641	-0.0141	0.1782	2.9261 ***	-0.3214	1.7155 *	0.0003
	Average	755.0	322.0	0.8426	1.8978	0.1360	-0.0087	0.1446				
	χ^2_6:(p-value)					<0.001	0.926	<0.001				
Returns with a 1-day lag	Average	755.0	321.2	0.8596	1.8297	0.1253	0.0105	0.1148				
	χ^2_6:(p-value)					<0.001	0.999	0.007				
Subperiod 80.1-87.9	Average	498.3	67.5	0.8012	1.0433	0.1748	0.1670	-0.0143[b]				
	χ^2_6:(p-value)					<0.001	0.826	<0.001				
Subperiod 87.11-96.12	Average	231.7	255.3	0.8412	1.9029	0.0777	-0.0713	0.1490				
	χ^2_6:(p-value)					0.008	0.920	0.270				

[a] For the variable-length moving average (VMA) and fixed-length moving average (FMA) rules, individual rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percent difference that is needed to generate a signal. For the trading range break (TRB) rules, individual rules are identified as (window, band) where window is the length of prior period in recording recent minimum and maximum price. For the FMA and TRB rules, the fixed 10-day holding periods after signals are assumed. Returns are for trades executed with a 0-day or 1-day lag. T statistics for the difference of the buy, sell, and buy-sell means from the unconditional means are based on the heteroskedasticity-consistent standard errors from the Cumby-Modest timing ability regression tests, and the significance for the t statistics is denoted by *, ** and *** at the 10 percent, 5 percent and 1 percent levels, respectively. Adj. R^2 is for the regression of the equity index returns on both buy and sell signals. The rows labeled Average report averages across all individual rules. The rows labeled χ^2_{10}:(p-value) report p-values for Wald test statistics testing the hypothesis that the conditional mean returns are equal to the unconditional mean returns across all individual rules.

[b] Among 6 individual rules, (150, 0.01) and (200, 0.01) do not generate any sell signals, and averages are calculated across the rules that generate signals. Consequently, average for buy-sell is negative and is not equal to buy average minus sell average. P-value for the Wald statistic is calculated using all 6 rules, whether rules generate sell signal.

Table 5

Test results for the technical trading rules applied to the Nikkei index futures (1990.12-1996.12)[a]

	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Panel A: Results for VMA rules												
Returns with a 0-day lag	(1, 50, 0)	627	737	1.2949	1.5396	0.0065	-0.0451	0.0516	0.6728	-0.6728	0.6728	-0.0004
	(1, 50, 0.01)	516	616	1.3186	1.6203	-0.0091	-0.0271	0.0181	0.2554	-0.1320	0.2014	-0.0007
	(1, 150, 0)	609	755	1.1991	1.5960	-0.0048	-0.0347	0.0300	0.3962	-0.3962	0.3962	-0.0006
	(1, 150, 0.01)	551	705	1.1777	1.6300	-0.0087	-0.0349	0.0262	0.2842	-0.3644	0.3356	-0.0007
	(5, 150, 0)	605	759	1.1860	1.6018	0.0044	-0.0419	0.0463	0.6133	-0.6133	0.6133	-0.0005
	(5, 150, 0.01)	562	708	1.1853	1.6404	0.0190	-0.0278	0.0468	0.9151	-0.1760	0.5467	-0.0005
	(1, 200, 0)	591	773	1.0952	1.6444	-0.0242	-0.0192	-0.0049	-0.0665	0.0665	-0.0665	-0.0007
	(1, 200, 0.01)	546	715	1.0756	1.6706	-0.0140	-0.0345	0.0205	0.1676	-0.3628	0.2780	-0.0007
	(2, 200, 0)	589	775	1.1013	1.6401	-0.0190	-0.0231	0.0041	0.0558	-0.0558	0.0558	-0.0007
	(2, 200, 0.01)	554	721	1.0681	1.6782	-0.0121	-0.0287	0.0166	0.2138	-0.2044	0.2145	-0.0007
	Average	575.0	726.4	1.1702	1.6261	-0.0062	-0.0317	0.0255				
	χ^2_{10}:(p-value)					0.996	0.999	0.999				
Returns with a 1-day lag	Average	575.0	725.4	1.1645	1.6335	0.0093	-0.0397	0.0490				
	χ^2_{10}:(p-value)					0.798	0.965	0.915				
Panel B: Results for FMA rules												
Returns with a 0-day lag	(1, 50, 0)	650	714	1.2904	1.5507	-0.0127	-0.0292	0.0166	0.2152	-0.2152	0.2152	-0.0007
	(1, 50, 0.01)	580	718	1.3212	1.5534	-0.0163	-0.0196	0.0033	0.1137	0.0474	0.0327	-0.0007
	(1, 150, 0)	620	744	1.1448	1.6340	-0.0111	-0.0299	0.0189	0.2501	-0.2501	0.2501	-0.0002
	(1, 150, 0.01)	600	738	1.1807	1.6173	0.0004	-0.0379	0.0383	0.5163	-0.4745	0.4983	-0.0006
	(5, 150, 0)	610	754	1.1423	1.6297	0.0003	-0.0389	0.0392	0.5210	-0.5210	0.5210	-0.0005
	(5, 150, 0.01)	590	736	1.1680	1.6301	0.0191	-0.0506	0.0697	0.9499	-0.8393	0.9004	-0.0002
	(1, 200, 0)	580	784	1.0765	1.6471	-0.0204	-0.0220	0.0016	0.0218	-0.0218	0.0218	-0.0007
	(1, 200, 0.01)	590	749	1.0868	1.6622	0.0016	-0.0427	0.0443	0.5453	-0.6322	0.5929	-0.0005
	(2, 200, 0)	580	784	1.0765	1.6471	-0.0204	-0.0220	0.0016	0.0218	-0.0218	0.0218	-0.0007
	(2, 200, 0.01)	590	748	1.0854	1.6664	0.0059	-0.0500	0.0559	0.6479	-0.8461	0.7518	-0.0004
	Average	599.0	746.9	1.1572	1.6238	-0.0054	-0.0343	0.0289				
	χ^2_{10}:(p-value)					0.994	0.992	0.993				
Returns with a 1-day lag	Average	599.0	745.9	1.1538	1.6255	-0.0097	-0.0319	0.0222				
	χ^2_{10}:(p-value)					0.998	0.995	0.997				

Table 5 (continued)

Panel C: Results for TRB rules												
	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Returns with a 0-day lag	(50, 0)	260	317	1.3670	1.6837	-0.0303	-0.0235	-0.0068	-0.1156	-0.0271	-0.0445	-0.0007
	(50, 0.01)	140	220	1.4126	1.8184	0.1406	-0.0021	0.1428	1.4349	0.1783	0.5950	-0.0004
	(150, 0)	120	200	1.1988	1.9193	0.0144	-0.0565	0.0709	0.3362	-0.2924	0.3887	-0.0006
	(150, 0.01)	80	160	1.3581	1.9720	-0.0427	-0.0199	-0.0229	-0.1455	0.0105	-0.0727	-0.0007
	(200, 0)	100	180	1.1656	1.9567	0.0385	-0.0013	0.0398	0.5250	0.1532	0.0860	-0.0007
	(200, 0.01)	60	140	1.1615	2.0323	0.0461	0.0451	0.0010	0.4583	0.4221	-0.2135	-0.0007
	Average	126.7	202.8	1.2773	1.8971	0.0278	-0.0097	0.0375				
	χ^2_6:(p-value)					0.996	0.999	0.999				
Returns with a 1-day lag	Average	126.7	202.7	1.2988	1.9082	0.0278	0.0580	0.0858				
	χ^2_6:(p-value)					0.850	0.988	0.946				

[a] For the variable-length moving average (VMA) and fixed-length moving average (FMA) rules, individual rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percent difference that is needed to generate a signal. For the trading range break (TRB) rules, individual rules are identified as (window, band) where window is the length of prior period in recording recent minimum and maximum price. For the FMA and TRB rules, the fixed 10-day holding periods after signals are assumed. Returns are for trades executed with a 0-day or 1-day lag. T statistics for the difference of the buy, sell, and buy-sell means from the unconditional means are based on the heteroskedasticity-consistent standard errors from the Cumby-Modest timing ability regression tests, and the significance for the t statistics is denoted by *, ** and *** at the 10 percent, 5 percent and 1 percent levels, respectively. Adj. R^2 is for the regression of the equity index returns on both buy and sell signals. The rows labeled Average report averages across all individual rules. The rows labeled χ^2_{10}:(p-value) report p-values for Wald test statistics testing the hypothesis that the conditional mean returns are equal to the unconditional mean returns across all individual rules.

are briefly explained below.

(a) Japan

Table 4 reports results for the Datastream Japan index. All three groups of the trading rules, the VMA, FMA and TRB rules, seem to be able to predict future returns on the Datastream Japan index. For the VMA and FMA rules, the averages across individual rules of the buy returns, sell returns and buy-sell spreads are significantly different from the unconditional values at the 1 percent level. When trades are executed with a 1-day lag, the averages across individual rules slightly decline, but are still significantly different from their unconditional values at the 1 percent level. Thus, the nonsynchronous trading is unlikely to explain away the forecast power of the VMA and FMA for the Datastream Japan index. However, the results are not robust across subperiods; the forecast power of the VMA and FMA only relies on the second subperiod. For the TRB rules, the averages across individual rules of the buy returns and buy-sell spreads are significantly different from zero at the 1 percent level, except for the buy-sell spreads of the second subperiod. However, the results on the sell returns indicate that sell signals virtually have no forecast power. These results are in contrast of the evidence of Bessembinder and Chan (1995), which indicates much weaker forecast power of the trading rules for Japan. The difference may be attributable to the difference in the sample period between two studies; while their sample cover the period 1975 - 1989, this thesis uses the sample from more recent period, 1980-1996.

Table 5 reports the results for the Nikkei index futures traded in the U.S. There are several motivations for examining the Nikkei index futures. First, futures contracts are not subject to problems related to the nonsynchronous trading of component securities in the index. Second, the effects of transaction costs are minimal for futures contracts. Third, the use of the U.S. traded instruments as a proxy for the Japanese market can avoid problems related to nonsynchronous trading hours across countries when the S&P 500 index, another U.S. traded instruments, is used as a proxy for the foreign market. The sample period is December 1990 - December 1996, which approximately corresponds to the second subperiod for the

Datastream Japan index.

Interestingly, neither individual rules nor averages across individual rules exhibit statistically significant forecast power for the Nikkei index futures. This result appears to indicate that the return on the Nikkei index futures follows different process from that of the Datastream Japan index. Many studies examine the deviation of the value of the stock index futures contract from the value of the underlying stock index (Stoll and Whaley 1986, 1990b; MacKinlay and Ramaswamy 1988; Lim 1990; Miller, Muthuswamy, and Whaley 1994) and the impact of the resulting arbitrage behaviour on the index returns (Stoll and Whaley 1987, 1990a, 1991; Merrick 1989; Brenner, Subrahmanyam, and Uno 1989, 1990; Karolyi 1996). Among them, Miller, Muthuswamy, and Whaley (1994) show that infrequent trading of component stocks in the index and random bid-ask bouncing of futures contract prices can cause the measured returns on the stock index and futures contract to appear to follow different process without resorting to the distorting price impact of stock index arbitragers. In the context of this thesis, the result that the trading rules exhibit significant forecast power for the Datastream Japan index but not for the Nikkei index futures may be attributable to the measurement errors that Miller, Muthuswamy, and Whaley (1994) emphasize. In fact, summary statistics in Table 1 indicate the significant positive autocorrelation for the Datastream Japan index and significant negative autocorrelation for the Nikkei index futures; the former is consistent with the positive autocorrelation induced by infrequent trading (Stoll and Whaley 1990b), and the latter is consistent with the negative autocorrelation induced by bid-ask bounce of the Nikkei index futures prices (Roll 1984).

Although the measurement errors may produce the difference in results between the Datastream Japan index and Nikkei index futures as a statistical illusion , infrequent trading itself can not completely explain the significant forecast power of the trading rules for the Datastream Japan index; a simple adjustment using trades with a 1-day lag has still led to statistically significant forecast power for the Datastream Japan index. However, the time-varying expected returns can be consistent with the trading rules' forecast power. Whether the observed profits are consistent with the time-varying expected returns implied by an asset pricing model is investigated later by using the bootstrap methodologies.

(b) U.S.

Table 6 reports the results for the Datastream U.S. index. Although BLL find that the same trading rules have significant forecast power for the Dow Jones index, the results for the Datastream U.S. index indicate that neither individual rules nor averages across individual rules exhibit statistically significant forecast power in a correct direction. In particular, as Panel C indicates, sell signals from the TRB rules predict future returns in an opposite direction; the mean sell returns based on the TRB rules are significantly higher than the unconditional mean returns.

Since the results may be attributable to the use of a different index, the trading rules are applied to the Dow Jones index during the period January 1980 - December 1996. Table 7 indicates that overall results are insensitive to selection of indices. For the overall period, the trading rules do not exhibit any significant forecast power in a correct direction. Although significant forecast power appears for the first subperiod for the VMA and FMA rules, it does not continue till the second subperiod. What is problematic is that the TRB rules tend to predict lower returns when buy signals are emitted and higher returns when sell signals are emitted; this is exactly opposite to what the trading rules are assumed to predict. Thus, investors would fail to forecast returns systematically, using the very same trading rules that were successful in the past. Froot and Perold (1995) provide evidence that the positive first autocorrelation of the daily U.S. stock index returns such the Dow Jones and S&P 500 indices has considerably declined in the 1980's. Their empirical results support the hypothesis that such decline of the positive autocorrelation is consistent with recent technological and institutional improvements in the processing of market-wide information. Insignificant forecast power of the technical trading rules for the U.S. indices observed over the recent period in this thesis may be due to improved dissemination of market-wide information as the results of Froot and Perold (1995) indicate. Bessembinder and Chan

Table 6

Test results for the technical trading rules applied to the Datastream U.S. equity market index (1980.1-1996.12)[a]

	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Panel A: Results for VMA rules												
Returns with a 0-day lag	(1, 50, 0)	2968	1267	0.7567	1.1404	0.0582	0.0487	0.0095	0.2709	-0.2709	0.2709	-0.0002
	(1, 50, 0.01)	2414	844	0.7739	1.2956	0.0622	0.0424	0.0198	0.5552	-0.3479	0.4776	-0.0002
	(1, 150, 0)	3347	888	0.7515	1.2807	0.0610	0.0342	0.0268	0.5971	-0.5971	0.5971	-0.0001
	(1, 150, 0.01)	3123	698	0.7493	1.3840	0.0629	0.0383	0.0246	0.7562	-0.3780	0.5851	-0.0001
	(5, 150, 0)	3356	879	0.7557	1.2760	0.0561	0.0523	0.0038	0.0854	-0.0854	0.0854	-0.0002
	(5, 150, 0.01)	3127	684	0.7597	1.1554	0.0517	0.0869	-0.0352	-0.3681	0.8122	-0.6234	-0.0001
	(1, 200, 0)	3407	828	0.7529	1.3072	0.0639	0.0202	0.0436	0.9247	-0.9247	0.9247	0.0001
	(1, 200, 0.01)	3263	710	0.7453	1.3755	0.0655	0.0308	0.0347	1.0426	-0.5549	0.8186	0.0001
	(2, 200, 0)	3405	830	0.7505	1.3122	0.0613	0.0310	0.0302	0.6394	-0.6394	0.6394	-0.0001
	(2, 200, 0.01)	3269	705	0.7517	1.3791	0.0608	0.0398	0.0210	0.5688	-0.3497	0.4685	-0.0001
	Average	3167.9	833.3	0.7547	1.2906	0.0603	0.0425	0.0179				
	χ^2_{10}:(p-value)					0.941	0.980	0.965				
Returns with a 1-day lag	Average	3166.9	833.3	0.7956	1.1804	0.0504	0.0738	-0.0234				
	χ^2_{10}:(p-value)					0.956	0.963	0.963				
Subperiod 80.1-87.9	Average	1313.8	411.6	0.8414	0.8691	0.0774	0.0357	0.0417				
	χ^2_{10}:(p-value)					0.456	0.517	0.482				
Subperiod 87.11-96.12	Average	1767.4	293.9	0.6555	0.9242	0.0552	0.0816	-0.0264				
	χ^2_{10}:(p-value)					0.996	0.993	0.997				
Panel B: Results for FMA rules												
Returns with a 0-day lag	(1, 50, 0)	3015	1220	0.7656	1.1379	0.0524	0.0626	-0.0102	-0.2884	0.2884	-0.2884	-0.0002
	(1, 50, 0.01)	2778	1120	0.7680	1.1757	0.0494	0.0675	-0.0181	-0.5393	0.4382	-0.4987	-0.0002
	(1, 150, 0)	3425	810	0.8625	0.9932	0.0504	0.0763	-0.0259	-0.6832	0.6832	-0.6832	-0.0001
	(1, 150, 0.01)	3301	810	0.8525	1.0437	0.0495	0.0832	-0.0337	-0.7310	0.8741	-0.8115	-0.0000
	(5, 150, 0)	3355	880	0.8684	0.9627	0.0468	0.0880	-0.0412	-1.1528	1.1528	-1.1528	0.0001
	(5, 150, 0.01)	3279	740	0.8398	1.1283	0.0401	0.1020	-0.0619	-1.8385	1.2926	-1.5921	0.0006
	(1, 200, 0)	3415	820	0.8606	0.9985	0.0501	0.0771	-0.0270	-0.7137	0.7137	-0.7137	-0.0001
	(1, 200, 0.01)	3358	790	0.8299	1.1187	0.0575	0.0610	-0.0035	0.2664	0.1651	0.0520	-0.0002
	(2, 200, 0)	3415	820	0.8612	0.9963	0.0524	0.0675	-0.0150	-0.3979	0.3979	-0.3979	-0.0002
	(2, 200, 0.01)	3357	760	0.8298	1.1330	0.0564	0.0687	-0.0122	0.1332	0.3743	-0.1203	-0.0002
	Average	3269.8	877.0	0.8338	1.0688	0.0505	0.0754	-0.0249				
	χ^2_{10}:(p-value)					0.740	0.867	0.815				
Returns with a 1-day lag	Average	3268.8	877.0	0.8368	1.0610	0.0489	0.0806	-0.0318				
	χ^2_{10}:(p-value)					0.501	0.597	0.554				
Subperiod 80.1-87.9	Average	1352.9	435.0	0.8378	0.8710	0.0707	0.0553	0.0154				
	χ^2_{10}:(p-value)					0.830	0.974	0.921				
Subperiod 87.11-96.12	Average	1818.8	319.0	0.6635	0.8835	0.0500	0.1021	-0.0524				
	χ^2_{10}:(p-value)					0.206	0.306	0.253				

Table 6 (continued)

	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
Panel C: Results for TRB rules												
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Returns with a 0-day lag	(50, 0)	1620	430	0.7554	1.5619	0.0479	0.0589	-0.0110	-0.4538	0.0518	-0.2831	-0.0002
	(50, 0.01)	600	200	0.8327	2.0713	0.0634	-0.0613	0.1247	0.2540	-0.8351	0.7577	0.0001
	(150, 0)	1340	150	0.7320	1.6434	0.0519	0.3482	-0.2963	-0.1896	2.2589 **	-1.3900	0.0006
	(150, 0.01)	460	90	0.7862	1.8264	0.0695	0.2690	-0.1994	0.4037	1.1374	-0.5131	-0.0001
	(200, 0)	1320	140	0.7285	1.6792	0.0490	0.3644	-0.3153	-0.3425	2.2502 **	-1.4926	0.0005
	(200, 0.01)	450	80	0.7718	1.8993	0.0634	0.3248	-0.2614	0.2303	1.2991	-0.7402	-0.0004
	Average	965.0	181.7	0.7678	1.7802	0.0575	0.2173	-0.1598				
	χ^2_6:(p-value)					0.996	0.032	0.466				
Returns with a 1-day lag	Average	965.0	181.7	0.7702	1.7713	0.0509	0.1703	-0.1194				
	χ^2_6:(p-value)					0.928	0.088	0.377				
Subperiod 80.1-87.9	Average	420.0	96.7	0.8582	0.9710	0.0764	0.1982	-0.1218				
	χ^2_6:(p-value)					0.998	0.098	0.947				
Subperiod 87.11-96.12	Average	523.3	66.7	0.6339	1.2698	0.0449	0.1760	-0.1312				
	χ^2_6:(p-value)					0.775	0.741	0.540				

[a] For the variable-length moving average (VMA) and fixed-length moving average (FMA) rules, individual rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percent difference that is needed to generate a signal. For the trading range break (TRB) rules, individual rules are identified as (window, band) where window is the length of prior period in recording recent minimum and maximum price. For the FMA and TRB rules, the fixed 10-day holding periods after signals are assumed. Returns are for trades executed with a 0-day or 1-day lag. T statistics for the difference of the buy, sell, and buy-sell means from the unconditional means are based on the heteroskedasticity-consistent standard errors from the Cumby-Modest timing ability regression tests, and the significance for the t statistics is denoted by *, ** and *** at the 10 percent, 5 percent and 1 percent levels, respectively. Adj. R^2 is for the regression of the equity index returns on both buy and sell signals. The rows labeled Average report averages across all individual rules. The rows labeled χ^2_{10}:(p-value) report p-values for Wald test statistics testing the hypothesis that the conditional mean returns are equal to the unconditional mean returns across all individual rules.

Table 7
Test results for the technical trading rules applied to Dow Jones index (1980.1-1996.12)[a]

	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Panel A: Results for VMA rules												
Returns with a 0-day lag	(1, 50, 0)	2832	1403	0.8345	1.2598	0.0399	0.0552	-0.0153	-0.4122	0.4122	-0.4122	-0.0002
	(1, 50, 0.01)	2300	942	0.8602	1.4290	0.0417	0.0457	-0.0040	-0.2272	0.0205	-0.1272	-0.0002
	(1, 150, 0)	3175	1060	0.8331	1.3720	0.0539	0.0180	0.0359	0.8049	-0.8049	0.8049	0.0000
	(1, 150, 0.01)	2986	874	0.8351	1.4672	0.0526	0.0168	0.0358	0.6493	-0.6870	0.6839	0.0000
	(5, 150, 0)	3189	1046	0.8332	1.3778	0.0481	0.0353	0.0128	0.2833	-0.2833	0.2833	-0.0002
	(5, 150, 0.01)	3005	864	0.8334	1.4684	0.0418	0.0223	0.0195	-0.2658	-0.5480	0.1477	-0.0002
	(1, 200, 0)	3279	956	0.8273	1.4297	0.0553	0.0096	0.0456	0.9426	-0.9426	0.9426	0.0001
	(1, 200, 0.01)	3126	827	0.8285	1.5076	0.0525	-0.0019	0.0544	0.6655	-1.0724	0.8852	0.0001
	(2, 200, 0)	3284	951	0.8288	1.4294	0.0513	0.0232	0.0281	0.5787	-0.5787	0.5787	-0.0001
	(2, 200, 0.01)	3128	822	0.8302	1.4994	0.0537	0.0063	0.0474	0.7671	-0.8862	0.8427	0.0001
	Average	3030.4	974.5	0.8344	1.4240	0.0491	0.0231	0.0260				
	χ^2_{10}:(p-value)					0.960	0.902	0.942				
Returns with a 1-day lag	Average	3029.4	974.5	0.8491	1.3345	0.0435	0.0428	0.0007				
	χ^2_{10}:(p-value)					0.973	0.977	0.975				
Subperiod 80.1-87.9	Average	1283.1	461.3	0.9276	0.8904	0.0695	0.0007	0.0688				
	χ^2_{10}:(p-value)					0.041	0.003	0.013				
Subperiod 87.11-96.12	Average	1673.4	372.5	0.7249	0.9427	0.0434	0.0843	-0.0409				
	χ^2_{10}:(p-value)					0.785	0.821	0.801				
Panel B: Results for FMA rules												
Returns with a 0-day lag	(1, 50, 0)	2825	1410	0.8402	1.2503	0.0342	0.0664	-0.0322	-0.8738	0.8738	-0.8738	0.0000
	(1, 50, 0.01)	2654	1260	0.8494	1.2934	0.0212	0.0870	-0.0658	-1.8509 *	1.5127	-1.7103 *	0.0007
	(1, 150, 0)	3175	1060	0.9918	1.0073	0.0384	0.0647	-0.0263	-0.7383	0.7383	-0.7383	-0.0001
	(1, 150, 0.01)	3141	950	0.9899	1.0538	0.0352	0.0697	-0.0345	-1.0728	0.8344	-0.9645	0.0004
	(5, 150, 0)	3175	1060	0.9893	1.0146	0.0393	0.0620	-0.0228	-0.6367	0.6367	-0.6367	-0.0001
	(5, 150, 0.01)	3129	910	0.8292	1.4514	0.0443	0.0364	0.0079	-0.0606	-0.2167	0.0797	-0.0002
	(1, 200, 0)	3245	990	0.9804	1.0445	0.0445	0.0464	-0.0019	-0.0514	0.0514	-0.0514	-0.0002
	(1, 200, 0.01)	3238	910	0.9664	1.1124	0.0463	0.0366	0.0097	0.1468	-0.2627	0.2059	-0.0002
	(2, 200, 0)	3245	990	0.9811	1.0423	0.0417	0.0557	-0.0141	-0.3767	0.3767	-0.3767	-0.0002
	(2, 200, 0.01)	3227	910	0.9489	1.1653	0.0443	0.0493	-0.0050	-0.0704	0.1332	-0.1025	-0.0002
	Average	3105.4	1045.0	0.9367	1.1435	0.0389	0.0574	-0.0185				
	χ^2_{10}:(p-value)					0.775	0.893	0.834				
Returns with a 1-day lag	Average	3104.4	1045.0	0.9399	1.1087	0.0378	0.0641	-0.0263				
	χ^2_{10}:(p-value)					0.636	0.693	0.667				
Subperiod 80.1-87.9	Average	1313.5	483.1	0.9181	0.9092	0.0611	0.0120	0.0380				
	χ^2_{10}:(p-value)					0.052	0.031	0.038				
Subperiod 87.11-96.12	Average	1727.4	405.0	0.7315	0.9057	0.0389	0.1000	-0.0061				
	χ^2_{10}:(p-value)					0.0651	0.069	0.065				

Table 7 (continued)

Panel C: Results for TRB rules												
	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Returns with a 0-day lag	(50, 0)	1502	490	0.8561	1.6287	-0.0068	0.0732	-0.0800	-2.6720 ***	0.4257	-1.7520 *	0.0009
	(50, 0.01)	580	220	0.8687	2.2552	0.0707	-0.0317	0.1024	0.7502	-0.5307	0.7718	0.0001
	(150, 0)	1272	200	0.8285	1.5350	-0.0023	0.2842	-0.2866	-2.2317 **	2.2971 **	-2.8760 ***	0.0026
	(150, 0.01)	460	90	0.8751	1.9468	0.0769	0.3188	-0.2419	0.8142	1.3672	-0.3701	-0.0002
	(200, 0)	1232	180	0.8257	1.5877	0.0046	0.3032	-0.2986	-1.8713 *	2.2674 **	-2.6061	0.0017
	(200, 0.01)	450	80	0.8653	2.0452	0.0762	0.3289	-0.2527	0.7969	1.2711	-0.3254	0.0013
	Average	916.0	210.0	0.8532	1.8331	0.0365	0.2128	-0.1762				
	χ^2_6:(p-value)					0.008	0.026	0.004				
Returns with a 1-day lag	Average	915.5	210.0	0.8578	1.8232	0.0302	0.1214	-0.0911				
	χ^2_6:(p-value)					0.147	0.239	0.075				
Subperiod 80.1-87.9	Average	413.3	125.0	0.9970	0.9594	0.0349	0.0925	-0.0576				
	χ^2_6:(p-value)					0.013	0.219	0.003				
Subperiod 87.11-96.12	Average	1727.4	405.0	0.7315	0.9057	0.0389	0.0999	-0.0611				
	χ^2_6:(p-value)					0.065	0.069	0.065				

[a] For the variable-length moving average (VMA) and fixed-length moving average (FMA) rules, individual rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percent difference that is needed to generate a signal. For the trading range break (TRB) rules, individual rules are identified as (window, band) where window is the length of prior period in recording recent minimum and maximum price. For the FMA and TRB rules, the fixed 10-day holding periods after signals are assumed. Returns are for trades executed with a 0-day or 1-day lag. T statistics for the difference of the buy, sell, and buy-sell means from the unconditional means are based on the heteroskedasticity-consistent standard errors from the Cumby-Modest timing ability regression tests, and the significance for the t statistics is denoted by *, ** and *** at the 10 percent, 5 percent and 1 percent levels, respectively. Adj. R^2 is for the regression of the equity index returns on both buy and sell signals. The rows labeled Average report averages across all individual rules. The rows labeled χ^2_{10}:(p-value) report p-values for Wald test statistics testing the hypothesis that the conditional mean returns are equal to the unconditional mean returns across all individual rules.

(1996) provide evidence that the trading rules which BLL examine do not work well for the Dow Jones index during the recent period 1976 - 1991. This thesis supplements their results by using the additional data in the 1990's and an alternative index for the U.S. equity market.

(c) Canada

Table 8 reports the results for the Datastream Canada index. All three groups of the VMA, FMA and TRB rules have significant forecast power for the Canada index; for trades with a 0-day lag for the overall period, the averages across individual rules of the buy returns, sell returns and buy-sell spreads are significantly different from the unconditional values at the 5 percent level. When trades are assumed to be executed with a 1-day lag, the forecast power of the FMA rules become insignificant as Panel B indicates. For the VMA and TRB rules, however, the averages across individual rules of the buy-sell spreads remain significant at the 5 percent level. Thus, at least the results for the VMA and TRB are unlikely to be explained away by the nonsynchronous trading. The results from subperiods confirm the robustness of the results for the VMA and TRB rules; the averages across individual rules of the buy-sell spreads still remain significant at the 5 percent level across two subperiods for the VMA and TRB rules. In contrast, for the FMA rules, the rules' forecast power for the overall period only relies on that of the first subperiod. The VMA rules' significant forecast power for the Canadian market is consistent with evidence provided by Ito (1996), who finds large differences between the mean buy and sell returns when the moving average rules are applied to the Toronto Stock Exchange 300 index.

The results for Canada are in a sharp contrast to those of the U.S. Fama (1991) emphasizes that if the predictability of returns arises due to time-varying expected returns, there exist common variations in the expected returns across assets and markets. Based on this intuition, Bessembinder and Chan (1995) argue that if the time-varying expected returns are responsible for the forecast power of the trading rules, the rules which can predict future returns for one market should have forecast power for another market to the extent to which

Table 8

Test results for the technical trading rules applied to the Datastream Canadian equity market index (1980.1-1996.12)[a]

	Trading rule	Nobs. Buy	Nobs. Sell	Std. dev. (%) Buy	Std. dev. (%) Sell	Mean return (%) Buy	Mean return (%) Sell	Mean return (%) Buy-Sell	t statistic Buy	t statistic Sell	t statistic Buy-Sell	Adj. R^2
Panel A: Results for VMA rules												
Returns with a 0-day lag	(1, 50, 0)	2681	1554	0.6381	0.8475	0.0720	-0.0223	0.0943	3.8070 ***	-3.8070 ***	3.8070 ***	0.0037
	(1, 50, 0.01)	2052	1076	0.6733	0.9509	0.0868	-0.0475	0.1343	4.3348 ***	-3.6669 ***	4.2678 ***	0.0055
	(1, 150, 0)	2894	1341	0.6293	0.8909	0.0628	-0.0173	0.0801	2.9694 ***	-2.9694 ***	2.9694 ***	0.0024
	(1, 150, 0.01)	2668	1068	0.6327	0.9604	0.0682	-0.0240	0.0922	3.3519 ***	-2.6181 ***	3.0762 ***	0.0029
	(5, 150, 0)	2905	1330	0.6295	0.8935	0.0572	-0.0058	0.0630	2.3223 **	-2.3223 **	2.3223 **	0.0014
	(5, 150, 0.01)	2656	1062	0.6361	0.9620	0.0600	-0.0055	0.0655	2.4541 **	-1.8169 *	2.1999 **	0.0014
	(1, 200, 0)	3016	1219	0.6254	0.9203	0.0587	-0.0152	0.0739	2.5733 **	-2.5733 **	2.5733 **	0.0019
	(1, 200, 0.01)	2782	1008	0.6315	0.9825	0.0604	-0.0250	0.0854	2.5988 ***	-2.4984 **	2.6158 ***	0.0022
	(2, 200, 0)	3022	1213	0.6240	0.9244	0.0557	-0.0081	0.0638	2.2115 **	-2.2115 **	2.2115 **	0.0014
	(2, 200, 0.01)	2783	1012	0.6307	0.9767	0.0584	-0.0202	0.0786	2.3646 **	-2.3243 **	2.4111 **	0.0018
	Average	2745.9	1188.3	0.6351	0.9309	0.0640	-0.0191	0.0831				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Returns with a 1-day lag	Average	2744.9	1188.3	0.6370	0.9317	0.0568	-0.0030	0.0598				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Subperiod 80.1-87.9	Average	1247.8	481.9	0.7665	0.8328	0.0815	-0.0384	0.1199				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Subperiod 87.11-96.12	Average	1414.1	577.9	0.4947	0.5453	0.0543	0.0160	0.0383				
	χ^2_{10}:(p-value)					<0.001	0.011	<0.001				
Panel B: Results for FMA rules												
Returns with a 0-day lag	(1, 50, 0)	2615	1620	0.6494	0.8287	0.0501	0.0170	0.0330	1.3661	-1.3661	1.3661	0.0003
	(1, 50, 0.01)	2417	1260	0.6612	0.9088	0.0660	-0.0121	0.0781	2.8922 ***	-2.5141 **	2.7716 ***	0.0021
	(1, 150, 0)	2885	1350	0.6326	0.8865	0.0494	0.0119	0.0375	1.3979	-1.3979	1.3979	0.0003
	(1, 150, 0.01)	2797	1240	0.6350	0.9091	0.0565	0.0021	0.0544	2.1703 **	-1.7673 *	1.9926 **	0.0009
	(5, 150, 0)	2925	1310	0.6309	0.8961	0.0452	0.0201	0.0251	0.9188	-0.9188	0.9188	0.0000
	(5, 150, 0.01)	2743	1190	0.6874	0.8317	0.0470	0.0241	0.0229	1.1277	-0.6836	0.9271	0.0000
	(1, 200, 0)	3015	1220	0.7136	0.7472	0.0389	0.0338	0.0051	0.2024	-0.2024	0.2024	-0.0002
	(1, 200, 0.01)	2932	1080	0.6324	0.9570	0.0515	-0.0081	0.0596	1.6747 *	-1.9613 **	1.8390 *	0.0009
	(2, 200, 0)	3015	1220	0.7138	0.7467	0.0388	0.0340	0.0048	0.1903	-0.1903	0.1903	-0.0002
	(2, 200, 0.01)	2912	1090	0.6314	0.9543	0.0519	-0.0009	0.0529	1.7097 *	-1.6688 *	1.7104 *	0.0008
	Average	2825.6	1258.0	0.6588	0.8666	0.0495	0.0122	0.0373				
	χ^2_{10}:(p-value)					0.005	0.019	0.009				
Returns with a 1-day lag	Average	2824.6	1258.0	0.6725	0.8416	0.0462	0.0187	0.0275				
	χ^2_{10}:(p-value)					0.213	0.271	0.226				
Subperiod 80.1-87.9	Average	1263.4	514.7	0.7644	0.8278	0.0729	-0.0152	0.0880				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Subperiod 87.11-96.12	Average	1467.6	618.0	0.5036	0.5259	0.0441	0.0329	0.0112				
	χ^2_{10}:(p-value)					0.697	0.804	0.793				

Table 8 (continued)

Panel C: Results for TRB rules												
	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Returns with a 0-day lag	(50, 0)	1250	540	0.7154	1.1293	0.0928	-0.0684	0.1612	3.2476 ***	-2.4417 **	3.3718 ***	0.0041
	(50, 0.01)	340	240	0.9503	1.4618	0.1575	-0.1033	0.2609	2.4797 **	-1.5752	2.5936 ***	0.0041
	(150, 0)	980	210	0.7345	1.6095	0.0948	-0.1892	0.2839	2.8023 ***	-2.1428 **	3.0589 ***	0.0044
	(150, 0.01)	260	110	1.0165	1.7806	0.1249	-0.0221	0.1471	1.4597	-0.3610	1.1755	0.0008
	(200, 0)	940	180	0.7373	1.4185	0.0967	-0.1299	0.2267	2.8135 ***	-1.6494 *	2.8806 ***	0.0032
	(200, 0.01)	250	100	0.9960	1.7253	0.0940	0.0320	0.0619	0.9413	-0.0322	0.6269	0.0000
	Average	670.0	230.0	0.8583	1.5208	0.1101	-0.0802	0.1903				
	χ^2_6:(p-value)					<0.001	0.014	<0.001				
Returns with a 1-day lag	Average	670.0	230.0	0.8510	1.3983	0.0676	-0.0451	0.1126				
	χ^2_6:(p-value)					0.109	0.147	0.017				
Subperiod 80.1-87.9	Average	335.0	117.8	1.0246	1.0480	0.1345	-0.0267	0.1611				
	χ^2_6:(p-value)					0.003	0.095	0.001				
Subperiod 87.11-96.12	Average	325.0	95.0	0.5082	0.6663	0.0675	-0.0752	0.1427				
	χ^2_6:(p-value)					0.009	0.012	<0.001				

[a] For the variable-length moving average (VMA) and fixed-length moving average (FMA) rules, individual rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percent difference that is needed to generate a signal. For the trading range break (TRB) rules, individual rules are identified as (window, band) where window is the length of prior period in recording recent minimum and maximum price. For the FMA and TRB rules, the fixed 10-day holding periods after signals are assumed. Returns are for trades executed with a 0-day or 1-day lag. T statistics for the difference of the buy, sell, and buy-sell means from the unconditional means are based on the heteroskedasticity-consistent standard errors from the Cumby-Modest timing ability regression tests, and the significance for the t statistics is denoted by *, ** and *** at the 10 percent, 5 percent and 1 percent levels, respectively. Adj. R^2 is for the regression of the equity index returns on both buy and sell signals. The rows labeled Average report averages across all individual rules. The rows labeled χ^2_{10}:(p-value) report p-values for Wald test statistics testing the hypothesis that the conditional mean returns are equal to the unconditional mean returns across all individual rules.

Table 9

Test results for the technical trading rules applied to Datastream Indonesian equity market index (1990.4-1996.12)[a]

	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Panel A: Results for VMA rules												
Returns with a 0-day lag	(1, 50, 0)	925	636	0.9789	1.0401	0.1651	-0.1383	0.3033	5.8018 ***	-5.8018 ***	5.8018 ***	0.0209
	(1, 50, 0.01)	831	555	0.9886	1.0612	0.1575	-0.1586	0.3161	4.8438 ***	-5.7036 ***	5.5086 ***	0.0194
	(1, 150, 0)	889	672	0.9405	1.1029	0.0928	-0.0264	0.1191	2.2509 **	-2.2509 **	2.2509 **	0.0027
	(1, 150, 0.01)	855	621	0.9475	1.1187	0.0964	-0.0321	0.1285	2.3252 **	-2.2524 **	2.3298 **	0.0031
	(5, 150, 0)	889	672	0.9405	1.1039	0.0856	-0.0169	0.1024	1.9344 *	-1.9344 *	1.9344 *	0.0019
	(5, 150, 0.01)	854	624	0.9496	1.1186	0.0862	-0.0080	0.0942	1.8937 *	-1.5187	1.7342 *	0.0014
	(1, 200, 0)	917	644	0.9320	1.1214	0.0773	-0.0094	0.0867	1.6110	-1.6110	1.6110	0.0011
	(1, 200, 0.01)	892	610	0.9239	1.1176	0.0795	0.0028	0.0768	1.6650 *	-1.1647	1.4506	0.0008
	(2, 200, 0)	914	647	0.9312	1.1223	0.0702	0.0009	0.0694	1.2902	-1.2902	1.2902	0.0005
	(2, 200, 0.01)	888	613	0.9254	1.1109	0.0771	0.0103	0.0668	1.5539	-0.9447	1.2838	0.0005
	Average	885.4	629.4	0.9458	1.1018	0.0988	-0.0376	0.1363				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Returns with a 1-day lag	Average	884.4	629.4	0.9528	1.0968	0.0886	-0.0176	0.1062				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Panel B: Results for FMA rules												
Returns with a 0-day lag	(1, 50, 0)	901	660	1.0010	1.0224	0.1290	-0.0780	0.2069	3.9879 ***	-3.9879 ***	3.9879 ***	0.0095
	(1, 50, 0.01)	884	620	0.9999	1.0508	0.1305	-0.0887	0.2192	3.9686 ***	-4.0814 ***	4.0570 ***	0.0102
	(1, 150, 0)	891	670	0.9461	1.0992	0.0738	-0.0015	0.0753	1.4220	-1.4220	1.4220	0.0007
	(1, 150, 0.01)	890	640	0.9454	1.1215	0.0740	-0.0030	0.0770	1.4277	-1.3985	1.4161	0.0007
	(5, 150, 0)	871	690	0.9428	1.0993	0.0657	0.0110	0.0547	1.0401	-1.0401	1.0401	0.0001
	(5, 150, 0.01)	877	650	0.9436	1.1228	0.0727	0.0011	0.0716	1.3501	-1.2885	1.3222	0.0006
	(1, 200, 0)	911	650	0.9400	1.1121	0.0545	0.0233	0.0311	0.5814	-0.5814	0.5814	-0.0004
	(1, 200, 0.01)	887	660	0.9188	1.1142	0.0734	0.0175	0.0559	1.3862	-0.7788	1.0958	0.0002
	(2, 200, 0)	911	650	0.9362	1.1168	0.0391	0.0448	-0.0057	-0.1070	0.1070	-0.1070	-0.0006
	(2, 200, 0.01)	904	640	0.9260	1.1147	0.0665	0.0140	0.0525	1.1086	-0.8667	0.9991	0.0000
	Average	892.7	653.0	0.9500	1.0974	0.0779	-0.0060	0.0839				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Returns with a 1-day lag	Average	891.7	653.0	0.9469	1.1032	0.0704	0.0054	0.0650				
	χ^2_{10}:(p-value)					0.002	0.001	0.001				

Table 9 (continued)

Panel C: Results for TRB rules															
	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic						Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy		Sell		Buy-Sell		
Returns with a 0-day lag	(50, 0)	425	300	1.0412	1.1405	0.2178	-0.1571	0.3750	4.1438	***	-3.4500	***	4.6214	***	0.0151
	(50, 0.01)	280	200	1.0689	1.2304	0.2602	-0.1847	0.4449	3.8306	***	-2.8591	***	4.2676	***	0.0142
	(150, 0)	295	130	0.9139	1.2414	0.2518	-0.1011	0.3529	4.2858	***	-1.3939		3.7841	***	0.0093
	(150, 0.01)	180	60	0.9514	1.5679	0.3233	-0.3649	0.6882	4.2014	***	-2.0890	**	4.2387	***	0.0146
	(200, 0)	265	110	0.9594	1.2658	0.2320	-0.1926	0.4246	3.5138	***	-2.0488	**	3.7213	***	0.0094
	(200, 0.01)	150	60	0.9827	1.5568	0.3563	-0.3137	0.6700	4.1268	***	-1.8387	*	4.0102	***	0.0136
	Average	265.8	143.3	0.9862	1.3338	0.2736	-0.2190	0.4926							
	χ^2_6:(p-value)					<0.001	<0.001	<0.001							
Returns with a 1-day lag	Average	265.3	143.3	0.9678	1.3779	0.2063	-0.1500	0.3563							
	χ^2_6:(p-value)					<0.001	<0.001	<0.001							

[a] For the variable-length moving average (VMA) and fixed-length moving average (FMA) rules, individual rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percent difference that is needed to generate a signal. For the trading range break (TRB) rules, individual rules are identified as (window, band) where window is the length of prior period in recording recent minimum and maximum price. For the FMA and TRB rules, the fixed 10-day holding periods after signals are assumed. Returns are for trades executed with a 0-day or 1-day lag. T statistics for the difference of the buy, sell, and buy-sell means from the unconditional means are based on the heteroskedasticity-consistent standard errors from the Cumby-Modest timing ability regression tests, and the significance for the t statistics is denoted by *, ** and *** at the 10 percent, 5 percent and 1 percent levels, respectively. Adj. R^2 is for the regression of the equity index returns on both buy and sell signals. The rows labeled Average report averages across all individual rules. The rows labeled χ^2_{10}:(p-value) report p-values for Wald test statistics testing the hypothesis that the conditional mean returns are equal to the unconditional mean returns across all individual rules.

Table 10

Test results for the technical trading rules applied to Datastream Mexican equity market index (1988.1-1996.12)[a]

		Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
	Trading rule	Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Panel A: Results for VMA rules												
Returns with a 0-day lag	(1, 50, 0)	1473	673	1.0895	1.5019	0.2041	-0.0410	0.2451	3.8039 ***	-3.8039 ***	3.8039 ***	0.0080
	(1, 50, 0.01)	1356	583	1.0983	1.5692	0.2223	-0.0531	0.2754	4.3721 ***	-3.5140 ***	4.0471 ***	0.0096
	(1, 150, 0)	1721	425	1.1268	1.6145	0.1409	0.0720	0.0688	0.8310	-0.8310	0.8310	0.0000
	(1, 150, 0.01)	1676	369	1.1243	1.6399	0.1471	0.0704	0.0767	1.1666	-0.7679	0.9991	0.0003
	(5, 150, 0)	1726	420	1.1460	1.5636	0.1390	0.0790	0.0599	0.7394	-0.7394	0.7394	-0.0001
	(5, 150, 0.01)	1668	370	1.1312	1.6176	0.1328	0.0483	0.0845	0.3296	-1.0801	0.7169	-0.0001
	(1, 200, 0)	1838	308	1.1566	1.6464	0.1372	0.0675	0.0698	0.7158	-0.7158	0.7158	-0.0001
	(1, 200, 0.01)	1806	271	1.1422	1.7096	0.1322	0.0662	0.0660	0.3357	-0.6521	0.5022	-0.0003
	(2, 200, 0)	1841	305	1.1568	1.6508	0.1324	0.0962	0.0362	0.3689	-0.3689	0.3689	-0.0004
	(2, 200, 0.01)	1806	271	1.1397	1.6805	0.1288	0.0905	0.0383	0.1077	-0.3986	0.2557	-0.0004
	Average	1691.1	399.5	1.1311	1.6194	0.1517	0.0496	0.1021				
	χ^2_{10}:(p-value)					<0.001	<0.001	<0.001				
Returns with a 1-day lag	Average	1690.1	399.5	1.1365	1.6103	0.1424	0.0833	0.0591				
	χ^2_{10}:(p-value)					0.045	0.144	0.083				
Panel B: Results for FMA rules												
Returns with a 0-day lag	(1, 50, 0)	1466	680	1.1451	1.4164	0.1676	0.0402	0.1273	2.0550 **	-2.0550 **	2.0550 **	0.0018
	(1, 50, 0.01)	1452	660	1.1334	1.4542	0.1695	0.0245	0.1450	2.1142 **	-2.3290 **	2.2299 **	0.0023
	(1, 150, 0)	1736	410	1.1480	1.5663	0.1363	0.0886	0.0477	0.5819	-0.5819	0.5819	-0.0002
	(1, 150, 0.01)	1728	400	1.1509	1.5733	0.1390	0.0665	0.0725	0.7495	-0.8967	0.8251	0.0000
	(5, 150, 0)	1736	410	1.1559	1.5397	0.1454	0.0503	0.0951	1.1763	-1.1763	1.1763	0.0004
	(5, 150, 0.01)	1726	390	1.1569	1.5776	0.1280	0.1203	0.0076	0.0474	-0.0997	0.0738	-0.0005
	(1, 200, 0)	1846	300	1.1682	1.6077	0.1306	0.1065	0.0241	0.2493	-0.2493	0.2493	-0.0004
	(1, 200, 0.01)	1849	280	1.1762	1.5866	0.1337	0.0623	0.0714	0.4904	-0.7577	0.6271	-0.0002
	(2, 200, 0)	1846	300	1.1682	1.6077	0.1306	0.1065	0.0241	0.2493	-0.2493	0.2493	-0.0004
	(2, 200, 0.01)	1839	290	1.1675	1.6102	0.1394	0.0487	0.0908	0.8968	-0.9247	0.9169	0.0002
	Average	1722.4	412.0	1.1571	1.5540	0.1420	0.0715	0.0706				
	χ^2_{10}:(p-value)					0.275	0.185	0.226				
Returns with a 1-day lag	Average	1721.4	412.0	1.1604	1.5439	0.1401	0.0816	0.0585				
	χ^2_{10}:(p-value)					0.565	0.492	0.525				

Table 10 (continued)

Panel C: Results for TRB rules													
	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Returns with a 0-day lag	(50, 0)	830	280	1.0595	1.7422	0.2533	-0.0412	0.2945	3.9563 ***	-1.8059 *	3.4383 ***	0.0068
	(50, 0.01)	540	200	1.0931	1.8868	0.3248	-0.1398	0.4647	4.6501 ***	-2.1719 **	4.1982 ***	0.0109
	(150, 0)	600	60	1.0837	2.2486	0.2889	-0.2608	0.5497	4.0783 ***	-1.3811	3.7932 ***	0.0079
	(150, 0.01)	410	50	1.1124	2.2741	0.3224	-0.4732	0.7956	3.8498 ***	-1.9243 *	3.9608 ***	0.0088
	(200, 0)	550	30	1.0916	2.5988	0.3151	-0.2563	0.5713	4.4740 ***	-0.8324	4.0107 ***	0.0084
	(200, 0.01)	390	30	1.1053	2.5677	0.3361	-0.1027	0.4389	4.0214 ***	-0.5052	3.4315 ***	0.0061
	Average	553.3	108.3	1.0909	2.2197	0.3068	-0.2123	0.5191				
	χ^2_6:(p-value)					<0.001	0.024	<0.001				
Returns with a 1-day lag	Average	553.3	108.3	1.1055	2.1472	0.2349	-0.1055	0.3404				
	χ^2_6:(p-value)					<0.001	0.428	<0.001				

[a] For the variable-length moving average (VMA) and fixed-length moving average (FMA) rules, individual rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percent difference that is needed to generate a signal. For the trading range break (TRB) rules, individual rules are identified as (window, band) where window is the length of prior period in recording recent minimum and maximum price. For the FMA and TRB rules, the fixed 10-day holding periods after signals are assumed. Returns are for trades executed with a 0-day or 1-day lag. T statistics for the difference of the buy, sell, and buy-sell means from the unconditional means are based on the heteroskedasticity-consistent standard errors from the Cumby-Modest timing ability regression tests, and the significance for the t statistics is denoted by *, ** and *** at the 10 percent, 5 percent and 1 percent levels, respectively. Adj. R^2 is for the regression of the equity index returns on both buy and sell signals. The rows labeled Average report averages across all individual rules. The rows labeled χ^2_{10}:(p-value) report p-values for Wald test statistics testing the hypothesis that the conditional mean returns are equal to the unconditional mean returns across all individual rules.

Table 11

Test results for the technical trading rules applied to Datastream Taiwanese equity market index (1988.1-1996.12)[a]

	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Panel A: Results for VMA rules												
Returns with a 0-day lag	(1, 50, 0)	1051	1079	1.9872	2.4063	0.1119	-0.0967	0.2086	2.1852 **	-2.1852 **	2.1852 **	0.0018
	(1, 50, 0.01)	945	973	2.0438	2.4498	0.1336	-0.1054	0.2390	2.4140 **	-2.1008 **	2.3218 **	0.0022
	(1, 150, 0)	1095	1035	2.0023	2.4126	0.0629	-0.0537	0.1166	1.2106	-1.2106	1.2106	0.0002
	(1, 150, 0.01)	1059	993	2.0129	2.4402	0.0639	-0.0442	0.1081	1.1993	-0.9707	1.0953	0.0001
	(5, 150, 0)	1096	1034	2.0255	2.3921	0.0670	-0.0582	0.1252	1.3005	-1.3005	1.3005	0.0003
	(5, 150, 0.01)	1061	996	2.0197	2.4224	0.0709	-0.0468	0.1177	1.3465	-1.0258	1.1989	0.0002
	(1, 200, 0)	1099	1031	1.9354	2.4718	0.0574	-0.0483	0.1057	1.0941	-1.0941	1.0941	0.0001
	(1, 200, 0.01)	1074	993	1.9325	2.4821	0.0711	-0.0567	0.1278	1.3630	-1.2080	1.3022	0.0003
	(2, 200, 0)	1106	1024	1.9520	2.4603	0.0687	-0.0613	0.1299	1.3440	-1.3440	1.3440	0.0004
	(2, 200, 0.01)	1071	996	1.9615	2.4790	0.0690	-0.0580	0.1269	1.3160	-1.2370	1.2867	0.0003
	Average	1065.7	1015.4	1.9873	2.4417	0.0776	-0.0629	0.1406				
	χ^2_{10}:(p-value)					0.009	0.026	0.014				
Returns with a 1-day lag	Average	1064.7	1015.4	2.0032	2.4280	0.0880	-0.0720	0.1600				
	χ^2_{10}:(p-value)					<0.001	0.002	<0.001				
Panel B: Results for FMA rules												
Returns with a 0-day lag	(1, 50, 0)	1040	1090	2.0974	2.3122	0.1023	-0.0855	0.1878	1.9656 **	-1.9656 **	1.9656 **	0.0013
	(1, 50, 0.01)	1051	1040	2.1125	2.3300	0.0764	-0.0696	0.1459	1.4472	-1.5423	1.5002	0.0007
	(1, 150, 0)	1050	1080	2.0175	2.3845	0.0641	-0.0501	0.1142	1.1950	-1.1950	1.1950	0.0002
	(1, 150, 0.01)	1094	1020	2.0098	2.4141	0.0791	-0.0666	0.1457	1.5563	-1.4470	1.5049	0.0006
	(5, 150, 0)	1090	1040	2.0714	2.3479	0.0779	-0.0689	0.1469	1.5291	-1.5291	1.5291	0.0006
	(5, 150, 0.01)	1094	1020	2.0287	2.3930	0.0710	-0.0600	0.1310	1.3849	-1.3167	1.3552	0.0004
	(1, 200, 0)	1040	1090	1.9732	2.4171	0.0509	-0.0364	0.0874	0.9163	-0.9163	0.9163	-0.0001
	(1, 200, 0.01)	1113	1010	1.9623	2.4529	0.0506	-0.0456	0.0962	0.9592	-1.0165	0.9904	0.0000
	(2, 200, 0)	1070	1060	1.9927	2.4126	0.0414	-0.0293	0.0707	0.7369	-0.7369	0.7369	-0.0002
	(2, 200, 0.01)	1103	1020	1.9786	2.4401	0.0541	-0.0531	0.1072	1.0281	-1.1776	1.1042	0.0001
	Average	1074.5	1047.0	2.0244	2.3904	0.0668	-0.0565	0.1233				
	χ^2_{10}:(p-value)					0.065	0.061	0.063				
Returns with a 1-day lag	Average	1073.5	1047.0	2.0355	2.3801	0.0769	-0.0623	0.1391				
	χ^2_{10}:(p-value)					0.014	0.015	0.014				

Table 11 (continued)

Panel C: Results for TRB rules												
	Trading rule	Nobs.		Std. dev. (%)		Mean return (%)			t statistic			Adj. R^2
		Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	
Returns with a 0-day lag	(50, 0)	490	440	2.1764	2.6770	0.1811	-0.1101	0.2913	2.0200 **	-1.0698	1.8448 *	0.0015
	(50, 0.01)	340	380	2.3929	2.8248	0.3652	-0.0655	0.4307	3.0655 ***	-0.5712	2.1239 **	0.0025
	(150, 0)	260	220	2.3421	2.8678	0.1093	-0.2690	0.3783	0.7644	-1.5429	1.5338	0.0011
	(150, 0.01)	190	190	2.3031	3.0157	0.3528	-0.2170	0.5698	2.1873 **	-1.0968	2.0746 **	0.0025
	(200, 0)	220	200	2.2114	2.9528	0.0109	-0.3040	0.3149	0.0332	-1.6013	1.1856	0.0004
	(200, 0.01)	170	170	2.2392	3.1355	0.1508	-0.2849	0.4357	0.8808	-1.2941	1.4781	0.0011
	Average	278.3	266.7	2.2775	2.9123	0.1950	-0.2084	0.4034				
	χ^2_6:(p-value)					0.003	0.158	0.006				
Returns with a 1-day lag	Average	278.3	266.7	2.2990	2.9447	0.1610	-0.1836	0.3445				
	χ^2_6:(p-value)					0.027	0.278	0.032				

[a] For the variable-length moving average (VMA) and fixed-length moving average (FMA) rules, individual rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percent difference that is needed to generate a signal. For the trading range break (TRB) rules, individual rules are identified as (window, band) where window is the length of prior period in recording recent minimum and maximum price. For the FMA and TRB rules, the fixed 10-day holding periods after signals are assumed. Returns are for trades executed with a 0-day or 1-day lag. T statistics for the difference of the buy, sell, and buy-sell means from the unconditional means are based on the heteroskedasticity-consistent standard errors from the Cumby-Modest timing ability regression tests, and the significance for the t statistics is denoted by *, ** and *** at the 10 percent, 5 percent and 1 percent levels, respectively. Adj. R^2 is for the regression of the equity index returns on both buy and sell signals. The rows labeled Average report averages across all individual rules. The rows labeled χ^2_{10}:(p-value) report p-values for Wald test statistics testing the hypothesis that the conditional mean returns are equal to the unconditional mean returns across all individual rules.

both markets are integrated. Thus, the results for the Canada index can be interpreted as indirect evidence for the segmentation of the Canadian market from the U.S. market. Alternatively, market inefficiencies could have caused the forecast power of the trading rules for the Canada index. Later, this thesis will address whether the equilibrium asset pricing models under various market structures can explain the observed forecast power of the technical rules by using the bootstrap methodologies.

(d) Indonesia

Table 9 reports results for the Datastream Indonesia index. All three groups of the trading rules seem to have substantial forecast power for the Indonesia index. For all three groups of trading rules and trades with a 0-day lag, the averages across individual rules of the buy returns, sell returns and buy-sell spreads are significantly different from the unconditional values at the 1 percent level. When trades are executed with a 1-day lag to adjust for nonsynchronous trading, the averages across individual rules of the buy returns, sell returns and buy-sell spreads remain significantly different from the unconditional values at the 1 percent level.

(e) Mexico

Table 10 reports the results for the Datastream Mexico index. The VMA rules seem to have forecast power for the Mexico index. For trades with a 0-day lag, the averages across individual rules in the VMA rules are significantly different from the unconditional values at the 1 percent level. However, when trades are executed with a 1-day lag, the average across individual rules of the buy-sell spreads is significantly different from zero only at the 10 percent level. The result that the VMA rules' forecast power becomes weaker indicates the possibility that the VMA rules simply capture the spurious autocorrelations due to nonsynchronous trading. The FMA rules do not have significant forecast power for the Mexico index as Panel B indicates. The TRB rules exhibit significant forecast power for the Mexico index. When trades are executed with a 1-day lag, the average across individual rules of the buy-sell spreads remains significantly different from zero at the 1 percent level.

(f) Taiwan

Table 11 reports the results for the Datastream Taiwan index. Both VMA and TRB rules have significant forecast power for the Taiwan index; the averages across individual rules of the buy-sell spreads are significantly different from zero at the 5 percent level. When trades are executed with a 1-day lag, the averages across individual rules of the buy-sell spreads remain significantly different from zero at the 5 percent level. The forecast power of the FMA rules seem to be weaker than the VMA and TRB rules; The average across individual rules of the buy-sell spreads is significantly different from zero only at the 10 percent level for the FMA rules. Surprisingly, however, the average across individual rules of the buy-sell spreads becomes significantly different from zero at the 5 percent level, when trades are executed with a 1-day lag. The overall results are consistent with Bessembinder and Chan (1995), who find the trading rules' significant forecast power for Taiwan.

In summary, the technical trading rules which BLL examine have considerable forecast power for future returns for the Datastream Japan, Canada, Indonesia, Mexico and Taiwan indices. However, the trading rules do not exhibit any significant forecast power for the Nikkei index futures traded in the U.S., the Datastream U.S. index or the Dow Jones index. In particular, the results for the Dow Jones index are in contrast of those of BLL who find a large spread between buy and sell returns for the Dow Jones index, using the data up to 1986. The cross-sectional pattern of the results seems to indicate that the technical trading rules have stronger forecast power for the emerging markets than for the developed markets. For the buy-sell spread, the average values across all trading rules and three emerging markets is 0.2302% per day or 77.8%on an annual basis; the averages across all trading rules and the Japan and Canada indices is 0.1030% per day or 29.4% on an annual basis. If the buy-sell spreads for the U.S. indices are included, the averages for the developed markets will be much lower. The results from trades with a 1-day lag after initial emissions of signals still indicate significant forecast power for the indices for which the trading rules can predict future returns. Thus, the spurious autocorrelations due to nonsynchronous trading are unlikely to explain the technical rules' observed forecast power completely.

This thesis provides some information on the effects of transaction costs on the trading rule returns by comparing returns on the "double-or-out' strategy with returns on the buy-and-hold strategy. The double-or-out strategy is defined as follows: if a buy signal is emitted, the strategy requires an investor to borrow additional fund at an interest rate in order to increase a long position in the equity index by 100 percent; if a sell signal is emitted, the strategy requires an investor to liquidate any equity position and invest in the interest bearing assets; on days classified as neutral, the strategy simply holds a long position in the equity index. There are several motivations for the use of the double-or-out strategy. First, this strategy does not require short sales, which are not feasible because of governments' restrictions in some countries. Second, since Bessembinder and Chan (1995) use this strategy to evaluate economic significance of the trading rules, the use of the same strategy will facilitate comparisons between the results in this thesis and theirs.

Table 12 reports the numbers of trades implied by the trading rules and the break-even (round-trip) transaction costs which equate the cumulative returns on the double-or-out strategy with those of the buy-and-hold strategy. The break-even transaction costs are expressed as a percentage relative to the amount invested.

The mean break-even transaction costs for the emerging markets are much higher than those for the developed markets. For the VMA rules, the mean break-even transaction cost for trades with a 1-day lag for Indonesia is the lowest among the emerging markets, 2.81 percent, which is still higher than those of the developed markets. Similarly, for the TRB rules, the lowest break-even cost among the emerging markets (1.99 percent for trades with a 1-day lag for Taiwan) is still higher than those of the developed markets. For the FMA rules, although the break-even transaction costs for the Datastream Japan index are comparable to those of the emerging markets, those of Mexico and Taiwan are in an impressive range of more than 5 percent.

The grand averages of the break-even transaction costs across the three trading rule groups

Table 12

Number of trades implied by three trading rules and the mean breakeven transactions costs (in percent) for the double-or-out strategy relative to the buy-and-hold strategy[a]

Rule	Statistic	Japan	Nikkei Index Futures	U.S.	Dow Jones Index	Canada	Indonesia	Mexico	Taiwan
	Period	80.1-96.12	90.12-96.12	80.1-96.12	80.1-96.12	80.1-96.12	90.4-96.12	88.1-96.12	88.1-96.12
	Number of days in the period[b]	4235	1364	4235	4235	4235	1561	2146	2130
VMA	Number of trades								
	Buy	48.7	23.1	59.2	66.8	53.1	14.4	23.4	28.5
	Sell	46.6	25.0	50.0	54.7	49.1	14.7	21.1	29.1
	Breakeven cost (%)								
	0-day lag trades	2.22	0.62	1.52	1.17	1.88	3.52	3.58	2.89
	1-day lag trades	2.20	0.90	0.83	0.78	1.52	2.81	3.01	3.16
FMA	Number of trades								
	Buy	26.0	10.4	28.5	31.8	29.7	9.8	11.8	14.1
	Sell	25.1	12.0	25.1	26.5	27.0	9.8	9.6	13.4
	Breakeven cost (%)								
	0-day lag trades	3.49	1.36	1.55	0.93	1.78	3.20	7.27	5.06
	1-day lag trades	3.51	1.23	1.41	0.71	1.48	2.49	6.95	5.84
TRB	Number of trades								
	Buy	58.8	10.8	77.3	77.0	51.0	19.3	41.3	22.2
	Sell	31.0	19.3	16.2	18.7	20.2	12.7	9.8	23.8
	Breakeven cost (%)								
	0-day lag trades	1.01	0.21	0.12	-0.16	1.09	3.09	3.07	2.31
	1-day lag trades	0.88	0.56	0.13	-0.04	0.64	2.28	2.09	1.99
Grand average across 3 rule groups	Number of trades								
	Buy	44.5	14.8	55.0	58.5	44.6	14.5	25.5	21.6
	Sell	34.2	18.8	30.4	33.3	32.1	12.4	13.5	22.1
	Breakeven cost (%)								
	0-day lag trades	2.24	0.73	1.06	0.65	1.58	3.27	4.64	3.42
	1-day lag trades	2.20	0.90	0.79	0.48	1.21	2.53	4.02	3.66
Estimate of transaction cost (%)									
	Elkins/McSherry (1997)	0.94					2.21	1.59	2.05
	Hill (1993)	1.20	0.11	0.69	0.69				

[a] Number of trades (for buy and sell) denotes the average number of trades that would be generated by trading rules. The double-or-out strategy is defined as follows: on buy signals, borrow at the risk-free rate (proxied by own-country's interest rate) to hold 200 % of long position in the equity index; on sell signals, liquidate any equity holdings and invest 100 % of money in the risk-free asset; when no signals are generated, simply invest 100% in the equity index. The breakeven transactions cost is defined as the level of a transactions cost at which the cumulative returns on the double-or-out strategy are equal to those of the buy-and-hold strategy of the equity index. In this table, the mean round-trip breakeven costs (in percent) across individual rules for each of the VMA, FMA and TRB as well as the grand averages across the three rule groups are reported.

[b] The first 201 days are omitted to generate the first signal.

summarize the detailed results well. The averages of the three emerging markets are very high, compared with those of the developed markets; they range from 3.27% to 4.64% for 0-day lag trades and from 2.53% to 4.02% for 1-day lag trades. Among the developed markets, those of the Datastream Japan index are the highest, 2.24% and 2.20% for 0-day and 1-day lag trades, respectively. For Canada, the grand averages of the break-even costs are of moderate size, 1.6% and 1.2% for 0-day and 1-day lag trades, respectively. For the Datastream U.S. index, they are lower than those of 5 other countries (except for the Nikkei index futures), 1.06% and 0.79% for 0-day and 1-day lag trades, respectively. Those of the Dow Jones index are even lower than the Datastream U.S. index, 0.65% and 0.48%, respectively. Finally, the grand averages of the break-even costs for the Nikkei index futures are 0.73% and 0.90% for 0-day and 1-day lag trades, respectively.

The mean break-even transaction costs for Taiwan calculated in this thesis are higher than those calculated in Bessembinder and Chan (1995). They report 2.39, 0.74 and 1.51 percents for the VMA, FMA and TRB rules (for 0-day lag trades), respectively; in this thesis, the corresponding break-even transaction costs are 2.89, 5.06, and 2.31 percents, respectively. Similarly, the mean break-even transaction costs for Japan calculated in this thesis are higher than those calculated in Bessembinder and Chan (1995). They report 1.37, -0.02 and 0.41 percents for the VMA, FMA and TRB rules (for 0-day lag trades), respectively; in this thesis, the corresponding transaction costs are 2.22, 3.49, and 1.01 percents, respectively. The difference between the two studies may be attributable to the difference in the sample period; this thesis uses a more recent sample.

If these break-even transaction costs are compared with reasonable estimates of actual transaction costs on a country-by-country basis, useful information on the post-transaction cost profitability of the trading rules can be obtained. Hill (1993) reports the round-trip transaction costs of 1.20%, 0.11%, and 0.69% for Japan, the Nikkei index futures, and the U.S., which are estimated by Goldman Sachs. These transaction costs consist of commissions, market impact costs, and taxes and are estimated for large-scale institutional investors who invest 25 million U.S. dollars in indexed portfolios. The Nikkei index and S&P 500 index are used as the local indices to calculate transaction costs for trading a basket of stocks in each index. Elkins/McSherry Co., Inc. (1997) provides the estimates of transaction costs for various countries. They report 0.94%, 2.21%, 1.59%, and 2.05% for Japan, Indonesia, Mexico, and Taiwan, respectively (as of June 30, 1995).[8] These transaction costs consist of commissions, fees, and market impact costs and are estimated based on the transaction records of their customers including over 40 large U.S. pension funds, investment managers, banks, and brokers.

The estimates of transaction costs are listed in the last two rows of Table 12.[9] For Japan, the difference in transaction costs between Hill (1993) and Elkins/McSherry (1997) reflects the fact that the former includes taxes but the latter does not. Hamao and Hasbrouck (1995) describes institutional details on the Tokyo Stock Exchange and examines the behavior of intraday trades and quotes for individual stocks. They report the average bid-ask spreads of 0.66% and 0.83% for two stocks with high transaction volume, which are comparable to the estimated transaction costs in Hill (1993) and Elkins/McSherry (1997). However, the stocks of the firm ranked as the 413rd out of the 1200 firms listed in the Tokyo Stock Exchange (1st section) in terms of volume had the average bid-ask spread of 1.00%, which seems to be high, compared with the estimates of transaction costs in Hill (1993) and Elkins/McSherry (1997). When constructing Datastream indices, selection of individual stocks is based on the capitalization size (at least 75% of the total market value), and liquidity of individual stocks is not explicitly taken into account. This may indicate the possibility that the Datastream indices include relatively many stocks with low liquidity and consequently, trading a basket of stocks in the Datastream indices may be more expensive due to large bid-ask spreads of illiquid stocks than the estimated transaction costs in Hill (1993) and Elkins/McSherry (1997) would imply.

---

[8] Elkins/McSherry reports one-way transaction costs on a country-by-country basis. This thesis doubles them to obtain round-trip transaction costs.

[9] No estimates of transaction costs for Canada were available to this thesis.

For the Datastream Japan index, the break-even transaction costs for both 0-day and 1-day lag trades (2.24% and 2.20%, respectively) are considerably higher than both estimates. Thus, the double-or-out strategy using the technical trading rules appears to be profitable relative to the buy-and-hold strategy at least for large-scale investors. For the Datastream U.S. index, the break-even transaction cost for 0-day lag trades, 1.06%, is higher than the estimate of 0.69% in Hill (1993). However, when trades are executed with a 1-day lag, the break-even cost of 0.79% is close to the estimate. Considering the possible bias due to more small stocks in the Datastream U.S. index, the double-or-out strategy based on the trading rules may not be profitable relative to the buy and hold after the nonsynchronous trading and transaction costs are taken into account. The results for the Dow Jones index further confirm this conjecture. Since the Dow Jones index consists of highly liquid stocks, the estimate reported in Hill (1993) is directly applicable to the index. The break-even costs for both 0-day and 1-day lag trades (0.65% and 0.48%) are lower than the estimate of 0.69%. Thus, for the Dow Jones index, the double-or-out strategy using the technical rules is not profitable relative to the buy and hold after transaction costs. For the Nikkei index futures, the break-even costs for both 0-day and 1-day lag trades (0.73% and 0.90%, respectively) are higher than the estimate of 0.11%. This is somewhat surprising because the standard test results have not detected any significant forecast power for the Nikkei index futures. This result may indicate that although the forecast power of the trading rules is not statistically significant for the Nikkei index futures, the rules can produce economically significant profits relative to the buy and hold. Elkins/McSherry (1997) report estimates of transaction costs for the three emerging markets. The break-even transaction costs are much higher than the estimates for all emerging markets. Thus, the double-or-out strategy seems to be profitable relative to the buy-and-hold strategy for these emerging markets; in particular, the difference between the break-even cost and estimate for the Mexico index is the largest (more than 2.4% even for trades with a 1-day lag) among the three markets.

As an additional experiment, this thesis calculates excess returns on the double-or-out strategy over the buy-and-hold strategy at various levels of transaction costs. Table 13

Table 13

Annualized excess returns (in percent) for the double-or-out strategy relative to the buy-and-hold strategy at different levels of transaction costs (in percent) [a]

Rule		Transaction cost (%)	Japan	U.S.	Dow Jones Index	Canada	Indonesia	Mexico	Taiwan	Transaction cost (%)	Nikkei Index Futures
			80.1-96.12	80.1-96.12	80.1-96.12	80.1-96.12	90.4-96.12	88.1-96.12	88.1-96.12		90.12-96.12
VMA	0-day lag trades	0.5	8.37	3.87	1.94	7.16	15.58	16.63	14.55	0.10	3.36
		1.0	5.37	0.57	-1.65	3.98	12.92	13.65	10.74	0.20	2.46
		1.5	2.45	-2.62	-5.12	0.89	10.32	10.74	7.06	0.30	1.56
	1-day lag trades	0.5	7.57	0.41	-0.16	4.79	11.70	12.76	17.27	0.10	6.16
		1.0	4.59	-2.78	-3.67	1.68	9.12	9.87	13.37	0.20	5.23
		1.5	1.69	-5.86	-7.07	-1.34	6.61	7.06	9.60	0.30	4.31
FMA	0-day lag trades	0.5	8.17	2.09	-0.06	4.05	9.88	15.14	14.57	0.10	4.38
		1.0	6.55	0.49	-1.77	2.32	8.17	13.72	12.74	0.20	3.96
		1.5	4.95	-1.09	-3.44	0.62	6.49	12.31	10.93	0.30	3.53
	1-day lag trades	0.5	8.02	1.47	-0.67	3.01	7.44	14.10	16.86	0.10	3.55
		1.0	6.40	-0.13	-2.36	1.30	5.77	12.69	14.99	0.20	3.13
		1.5	4.81	-1.69	-4.03	-0.38	4.12	11.30	13.15	0.30	2.71
TRB	0-day lag trades	0.5	2.57	-2.05	-4.26	2.77	13.01	15.71	9.86	0.10	0.69
		1.0	-0.11	-4.72	-6.93	0.63	10.15	12.32	6.94	0.20	0.13
		1.5	-2.72	-7.31	-9.52	-1.46	7.36	9.03	4.09	0.30	-0.42
	1-day lag trades	0.5	1.81	-2.23	-3.63	0.92	9.20	9.45	8.30	0.10	2.62
		1.0	-0.86	-4.89	-6.31	-1.17	6.44	6.24	5.42	0.20	2.05
		1.5	-3.45	-7.48	-8.92	-3.23	3.75	3.12	2.61	0.30	1.49
Grand average across 3 rule groups	0-day lag trades	0.5	6.37	1.30	-0.79	4.66	12.82	15.83	12.99	0.10	2.81
		1.0	3.93	-1.22	-3.45	2.31	10.41	13.23	10.14	0.20	2.18
		1.5	1.56	-3.67	-6.03	0.02	8.06	10.69	7.36	0.30	1.56
	1-day lag trades	0.5	5.80	-0.12	-1.49	2.91	9.45	12.10	14.14	0.10	4.11
		1.0	3.38	-2.60	-4.12	0.60	7.11	9.60	11.26	0.20	3.47
		1.5	1.02	-5.01	-6.67	-1.65	4.83	7.16	8.45	0.30	2.84

[a] The double-or-out strategy is defined as follows: on buy signals, borrow at the risk-free rate (proxied by own-country's interest rate) to hold 200 % of long position in the equity index; on sell signals, liquidate any equity holdings and invest 100 % of money in the risk-free asset; when no signals are generated, simply invest 100% in the equity index. The mean annualized excess returns across all individual rules for each of the VMA, FMA, and TRB as well as the grand averages across the 3 rule groups are reported. Returns are for trades executed with a 0-day or 1-day lag. Annualization is based on 250 days per year.

presents annualized excess returns on the double-or-out strategy over the buy-and-hold strategy at the transaction costs of 0.5%, 1.0% and 1.5% for the equity market indices and at the transaction costs of 0.1%, 0.2%, and 0.3% for the Nikkei index futures. The average values across individual rules for each of the three trading rule groups as well as the grand averages across the three rule groups are reported. Again, the excess returns for the emerging markets are considerably large, compared with those for the developed markets. The results for the grand averages indicate that even for 1-day lag trades and at the transaction cost of 1.5%, the average annualized excess returns range from the lowest of 4.83% to the highest of 8.45% for the emerging markets. That is, the double-or-strategy would earn the annual excess profit of 4.83% over the buy and hold for the Indonesia index and 8.45% for the Taiwan index. Among the developed markets, annualized excess returns for the Datastream Japan index are positive and the largest at all transaction cost levels for the grand averages. For the Canada index, the grand averages of excess returns are positive at the transaction cost of 1.0%, however, they are almost zero or negative at the transaction cost of 1.5%. For the two U.S. indices, annualized excess returns are negative for most transaction cost levels. Finally, the results for the Nikkei index futures confirm economic significance of the trading rules; at the transaction cost of 0.2%, which almost doubles the estimate (0.11%) reported in Hill (1993), the double-or-out strategy leads to the annualized excess profits of 2.18% and 3.47% for 0-day and 1-day lag trades, respectively.

This analysis suggests that if investors could achieve transaction costs lower than the break-even transaction costs reported in Table 12, they would acquire excess profits over the buy-and-hold strategy, using the double-or-out strategy based on the technical trading rules. When comparing the returns on the double-or-out strategy with the returns on the buy-and-hold strategy, it is implicitly assumed that both strategies incur the same risk. However, the degree of the risk can be different between the buy-and-hold and double-or-out strategies, and the apparent excess profits, if any, may be a fair compensation for the higher risk that the double-or-out strategy would incur. Later, the relative riskiness of the technical trading rules is controlled in evaluating the profitability of the trading rules by using the bootstrap methodologies.

7.3 Estimation of the conditional asset pricing models

This thesis evaluates the technical trading rules by using asset pricing models with the time-varying expected returns. This thesis estimates three different types of asset pricing models corresponding to complete integration, mild segmentation and complete segmentation under a conditional mean-variance framework.

Under complete integration, the world CAPM holds. Under mild segmentation, the asset pricing model of Errunza and Losq (1985) holds, which is referred to as the mild segmentation APM (asset pricing model) in this chapter. Under complete segmentation, the purely domestic CAPM holds. Detailed specifications of the empirical models are already explained in Chapter 4. The results for each country are briefly explained below.

(a) Japan

Table 14 reports the parameter estimates of various models for the Japanese and foreign expected excess returns and the results from the likelihood ratio tests for a set of restrictions. The two systems of equations for the models are presented above Panel A. Details of notation are the same as ones given in Chapter 4. The world CAPM and mild segmentation APM are nested in unrestricted model 1. Thus, the restriction implied by the world CAPM ($\beta_{dv} = \beta_{dc} = \beta_{fv} = \beta_{fc}$) and the restriction implied by the mild segmentation APM ($\beta_{fv} = \beta_{fc}$) can be tested against unrestricted model 1 by using the likelihood ratio tests. Unrestricted model 2 is estimated to conduct the likelihood ratio test for the restriction implied by the domestic CAPM ($\beta_{dc} = \beta_{fc} = 0$). The main difference between unrestricted model 1 and 2 is that while the former contains market-value weights, the latter does not. Since returns on both the Japanese and foreign markets exhibit unusual behaviour on the days of the worldwide market crash in October 1987, dummy variables corresponding to

Table 14
Parameter estimates for the conditional equilibrium models of the daily expected excess returns for the Japanese and foreign equity markets [a]

Unrestricted model 1

$$r_{dt} = \alpha_d + \beta_{dw}\omega_{dt-1}h_{dt} + \beta_{dc}(1-\omega_{dt-1})h_{ct} + b_d' d + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{fw}\omega_{ft-1}h_{ft} + \beta_{fc}(1-\omega_{ft-1})h_{ct} + b_f' d + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

World CAPM: $\beta_{dw} = \beta_{dc} = \beta_{fw} = \beta_{fc}$

Mild segmentation APM: $\beta_{fw} = \beta_{fc}$

Unrestricted model 2

$$r_{dt} = \alpha_d + \beta_{dw}h_{dt} + \beta_{dc}h_{ct} + b_d' d + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{fw}h_{ft} + \beta_{fc}h_{ct} + b_f' d + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

Domestic CAPM: $\beta_{dc} = \beta_{fc} = 0$

Panel A: Period during 1980.1-1996.12

Conditional expected excess returns

Model		α_d	β_{dw}	β_{dc}	α_f	β_{fw}	β_{fc}	Log-likelihood
Unrestricted model 1	Estimate	0.0003	16.2628	-8.0060	0.0010	-12.1256	18.7266	30101.555
	Standard t-stat	1.97**	2.58**	-0.64	2.65**	-1.55	1.02	R^2_1 = 8.09%
	Robust t-stat	2.20**	3.34**	-0.84	2.86**	-1.67*	1.28	R^2_2 = 6.03%
World CAPM	Estimate	0.0004	4.9528	4.9528	0.0002	4.9528	4.9528	30097.583
	Standard t-stat	3.04**	1.22	1.22	0.94	1.22	1.22	R^2_1 = 7.77%
	Robust t-stat	3.08**	1.30	1.30	0.95	1.30	1.30	R^2_2 = 6.07%
Mild segmentation APM	Estimate	0.0003	15.8583	-11.0409	0.0007	-5.6249	-5.6249	30100.722
	Standard t-stat	2.11**	2.56**	-0.88	2.36**	-0.95	-0.95	R^2_1 = 8.08%
	Robust t-stat	2.67**	3.17**	-1.09	2.37**	-0.98	-0.98	R^2_2 = 6.00%
Unrestricted model 2	Estimate	0.0002	5.6390	-3.4648	0.0009	-8.6588	10.0289	30102.274
	Standard t-stat	1.40	2.61**	-0.42	2.61**	-1.57	1.54	R^2_1 = 8.14%
	Robust t-stat	1.37	2.67**	-0.42	2.61**	-1.65*	1.48	R^2_2 = 6.05%
Domestic CAPM	Estimate	0.0002	4.7991		0.0008	-4.7783		30100.845
	Standard t-stat	1.55	2.52**		2.37**	-0.97		R^2_1 = 8.09%
	Robust t-stat	1.89*	3.23**		2.24**	-0.95		R^2_2 = 6.01%

Conditional covariance dynamics

		C			A				G			
		C_{11}	C_{12}	C_{22}	A_{11}	A_{21}	A_{12}	A_{22}	G_{11}	G_{21}	G_{12}	G_{22}
Unrestricted model 1	Estimate	0.0013	0.0004	0.0012	0.3578	0.0279	0.0254	0.1870	0.9279	-0.0068	-0.0100	0.9716
	Standard t-stat	20.99**	2.52**	13.27**	42.68**	2.79**	3.43**	18.55**	302.19**	-1.80*	-3.59**	319.51**
	Robust t-stat	12.94**	2.80**	8.39**	23.81**	2.75**	2.57**	13.55**	149.29**	-1.86*	-2.63**	205.71**

Table 14 (continued)

Model		α_d	β_{dt}	β_{dk}	α_f	β_{ft}	β_{fk}	Log-likelihood
Panel B: Period during 1980.1-1987.9								
Unrestricted model 1	Estimate	0.0004	26.6897	14.3411	-0.0001	1.2359	308.2748	14056.748
	Standard t-stat	2.24**	2.13**	0.42	-0.16	0.10	3.38**	R^2_1 = 0.71%
	Robust t-stat	3.33**	2.13**	0.33	-0.16	0.11	2.89**	R^2_2 = 0.64%
World CAPM	Estimate	0.0005	11.2031	11.2031	-0.0003	11.2031	11.2031	14051.335
	Standard t-stat	3.42**	1.35	1.35	-0.71	1.35	1.35	R^2_1 = 0.71%
	Robust t-stat	4.49**	3.43**	3.43**	-4.68**	3.43**	3.43**	R^2_2 = 0.64%
Mild segmentation APM	Estimate	0.0004	29.6612	-25.3598	0.0003	-1.2639	-1.2639	14053.412
	Standard t-stat	2.29**	2.35**	-0.81	0.53	-0.11	-0.11	R^2_1 = 0.88%
	Robust t-stat	2.60**	2.93**	-0.60	0.59	-0.13	-0.13	R^2_2 = 6.91e-3%
Unrestricted model 2	Estimate	0.0003	9.3972	6.6536	0.0000	-0.1934	81.0099	14056.743
	Standard t-stat	1.37	2.03**	0.27	-0.02	-0.02	3.17**	R^2_1 = 0.68%
	Robust t-stat	1.50	1.90*	0.18	-0.02	-0.02	2.09**	R^2_2 = 0.51%
Domestic CAPM	Estimate	0.0002	10.5037		0.0003	-0.5202		14053.745
	Standard t-stat	1.19	2.38**		0.43	-0.05		R^2_1 = 0.77%
	Robust t-stat	1.31	2.88**		0.89	-0.12		R^2_2 = 1.62e-4%
Panel C: Period during 1987.11-1996.12								
Unrestricted model 1	Estimate	-0.0004	28.2421	-16.3990	0.0013	-21.2989	29.9311	15976.396
	Standard t-stat	-1.64	3.38**	-0.98	2.46**	-1.52	1.36	R^2_1 = 1.07%
	Robust t-stat	-1.78*	3.43**	-0.87	2.00**	-1.31	1.04	R^2_2 = 0.13%
World CAPM	Estimate	-0.0002	11.6327	11.6327	0.0001	11.6327	11.6327	15971.922
	Standard t-stat	-0.86	2.04**	2.04**	0.29	2.04**	2.04**	R^2_1 = 0.31%
	Robust t-stat	-1.28	3.45**	3.45**	0.44	3.45**	3.45**	R^2_2 = 0.09%
Mild segmentation APM	Estimate	-0.0004	27.8819	-19.2771	0.0008	-3.9522	-3.9522	15975.299
	Standard t-stat	-1.53	3.37**	-1.11	1.91*	-0.47	-0.47	R^2_1 = 1.00%
	Robust t-stat	-1.67*	3.60**	-1.31	1.68*	-0.41	-0.41	R^2_2 = 0.01%
Unrestricted model 2	Estimate	-0.0003	7.6388	-7.7937	0.0009	-7.8239	8.7024	15907.759
	Standard t-stat	-1.05	2.58**	-0.82	1.81*	-0.91	1.24	R^2_1 = 0.75%
	Robust t-stat	-1.08	2.01**	-0.71	1.47	-0.70	0.95	R^2_2 = 0.07%
Domestic CAPM	Estimate	-0.0003	5.9176		0.0006	0.1487		15906.618
	Standard t-stat	-0.96	2.27**		1.25	0.02		R^2_1 = 0.51%
	Robust t-stat	-0.86	1.81*		0.90	0.01		R^2_2 = 2.40e-5%

Panel D: Likelihood ratio tests for the World CAPM, mild segmentation APM and domestic CAPM restrictions

Restrictions	1980.1-1996.12			1980.1-1987.9			1987.11-1996.12		
	χ^2	df	P-value	χ^2	df	P-value	χ^2	df	P-value
World CAPM	7.943	3	0.047	10.825	3	0.013	8.948	3	0.030
Mild Segmentation APM	1.664	1	0.197	6.672	1	0.010	2.194	1	0.139
Domestic CAPM	2.856	2	0.240	5.996	2	0.014	2.282	2	0.320

* Maximum likelihood estimates for the various conditional models are obtained, using the daily Japanese and foreign equity market excess returns, r_{dt} and r_{ft}. All excess returns are denominated by yen and are computed net of the Japanese call rate. The market value-weights for Japanese and foreign equity markets on day t are denoted by ω_{dt} and ω_{ft}, respectively. *b* is a vector of parameters and *d* is a vector of the dummy variables which correspond to the days of market crash, October 16 19, 20 and 21 in 1987. R^2_1 and R^2_2 denote the ratio of the explained to total variation in the excess returns associated with the Japanese and foreign equity markets. Robust t statistics are computed with quasi-maximum-likelihood methods. Significance for t statistics is denoted by * and ** at the 10 percent and 5 percent levels.

October 16, 19, 20 and 21 in 1987 are included in both conditional-expected-return equations, following the CKS (1992) study.

Panel A reports the results for the overall period January 1980 - December 1996. The parameter estimates for the conditional covariance dynamics are reported only for unrestricted model 1 to save the space. Panel B and C report the parameter estimates of the conditional-expected-return equations for two subperiods, January 1980 - September 1987, and November 1987 - December 1996. Since October 1987, the month of the market crash, is excluded from estimations for subperiods, dummy variables for the days of the market crash are not included in the models. In Panel B and C, parameter estimates for the conditional covariance dynamics are not reported to save the space. Finally, Panel D reports the results from the likelihood ratio tests for the restrictions implied by the world CAPM, mild segmentation APM and domestic CAPM.

The Datastream Japan index is used to compute returns on the Japanese equity market. Returns on the foreign market are computed by using data on the Datastream world index and the market-value weights for the Japan index. All excess returns are denominated by yen and are computed net of the Japanese interbank call rate.

Panel A shows the results for the overall period. The conditional variance of the Japanese market returns has a significant positive effect on Japanese conditional expected returns across all models that do not impose any restrictions on a coefficient for the conditional variance. In contrast, the conditional covariance of the Japanese market with the foreign market has no effect. Panel B and C indicate that similar results hold across subperiods. These results are consistent with those of CKS; they find a significant positive effect of the variance of the Japanese returns on the Japanese expected returns in a bivariate setting of the U.S. versus Japanese markets. The significant variance effect and insignificant covariance effect seem to be favourable to the mild segmentation APM and domestic CAPM and against the world CAPM. Panel D shows the results from the likelihood ratio tests. The world

CAPM is rejected at the 5 percent level for the overall period and both subperiods. While both the mild segmentation APM and domestic CAPM are rejected at the 5 percent level for the first subperiod, neither of the two models is rejected for the overall period and second subperiod. This analysis seems to suggest that Japan is not completely integrated over the sample period in this thesis. This result is consistent with that of Harvey (1991); the joint hypothesis of the integration and world CAPM is rejected for Japan in his study.

Table 15 reports the parameter estimates for the various models with the U.S.-traded Nikkei index futures as a proxy for the Japanese market and the S&P 500 as a proxy for the foreign market. Since the sample period is December 1990 - December 1996, dummy variables for the days of the market crash are not included in the system of equations. All excess returns are denominated by yen and are computed net of the Japanese interbank call rate. The results in Panel A indicate that the variance of the Japanese market does not have a significant positive effect on the Japanese expected returns, except for the domestic CAPM, while the covariance has a significant positive effect on the Japanese expected returns for unrestricted model 1 and the mild segmentation APM at the 10 percent level, when robust t statistics are used. When standard t statistics are used, none of the coefficients for the variance and covariance in the Japanese conditional-expected-return equation are significantly different from zero. The results from the likelihood ratio tests in Panel C indicate the lack of power in the test statistics; none of the three models are rejected at a conventional level.

(b) U.S.

Table 16 reports the parameter estimates of various models for the U.S. and foreign expected returns and the results from likelihood ratio tests for a set of restrictions. The Datastream U.S. index is used to compute returns on the U.S. equity market. Returns on the foreign market are computed, using data on the Datastream world index and the market-value weights for the U.S. index. All excess returns are denominated by U.S. dollars and are computed net of the U.S. Treasury bill rate.

Table 15

Parameter estimates for the conditional equilibrium models of the daily expected excess returns for the Nikkei index futures and S&P 500 (1990.12-1996.12)[a]

Unrestricted model 1

$$r_{dt} = \alpha_d + \beta_{dd}\omega_{d,t-1}h_{dt} + \beta_{dc}(1-\omega_{d,t-1})h_{ct} + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{ff}\omega_{f,t-1}h_{ft} + \beta_{fc}(1-\omega_{f,t-1})h_{ct} + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

World CAPM: $\beta_{dd} = \beta_{dc} = \beta_{ff} = \beta_{fc}$

Mild segmentation APM: $\beta_{ff} = \beta_{fc}$

Unrestricted model 2

$$r_{dt} = \alpha_d + \beta_{dd}h_{dt} + \beta_{dc}h_{ct} + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{ff}h_{ft} + \beta_{fc}h_{ct} + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

Domestic CAPM: $\beta_{dc} = \beta_{fc} = 0$

Panel A: Conditional expected excess returns

Model		α_d	β_{dd}	β_{dc}	α_f	β_{ff}	β_{fc}	Log-likelihood
Unrestricted model 1	Estimate	-0.0023	0.7824	74.4238	-0.0087	124.4943	77.6756	9703.960
	Standard t-stat	-1.67*	0.05	1.47	-2.92**	2.64**	1.01	$R^2_1 = 0.25\%$
	Robust t-stat	-2.00**	0.06	1.69*	-1.78*	1.75*	0.96	$R^2_2 = 0.65\%$
World CAPM	Estimate	-0.0009	10.9847	10.9847	-0.0005	10.9847	10.9847	9701.741
	Standard t-stat	-1.13	1.07	1.07	-0.62	1.07	1.07	$R^2_1 = 0.10\%$
	Robust t-stat	-1.22	1.11	1.11	-0.63	1.11	1.11	$R^2_2 = 0.01\%$
Mild segmentation APM	Estimate	-0.0023	2.9261	74.1221	-0.0083	111.5482	111.5482	9703.859
	Standard t-stat	-1.71*	0.21	1.45	-2.90**	2.95*	2.95**	$R^2_1 = 0.26\%$
	Robust t-stat	-1.93*	0.27	1.89*	-1.81*	1.91*	1.91*	$R^2_2 = 0.64\%$
Unrestricted model 2	Estimate	-0.0019	1.6788	40.3487	-0.0136	150.6931	7.2819	9703.921
	Standard t-stat	-1.21	0.36	0.83	-2.25**	2.04**	0.25	$R^2_1 = 0.18\%$
	Robust t-stat	-1.28	0.26	0.70	-0.48	0.46	0.16	$R^2_2 = 0.66\%$
Domestic CAPM	Estimate	-0.0007	4.0409		-0.0134	152.3636		9703.548
	Standard t-stat	-1.16	1.17		-2.43**	2.44**		$R^2_1 = 0.13\%$
	Robust t-stat	-2.58**	1.97**		-39.08**	40.55**		$R^2_2 = 0.59\%$

Panel B: Conditional covariance dynamics

		C			A				G			
		C_{11}	C_{12}	C_{22}	A_{11}	A_{21}	A_{12}	A_{22}	G_{11}	G_{21}	G_{12}	G_{22}
Unrestricted model 1	Estimate	0.0019	0.0008	-0.0009	0.2654	-0.0817	0.0156	0.0636	0.9575	0.0014	-0.0031	0.9906
	Standard t-stat	5.06**	0.95	-1.04	15.56**	-2.37**	1.44	4.21**	209.76**	0.06	-0.91	146.01**
	Robust t-stat	4.13**	0.40	-0.78	6.55**	-1.47	1.18	2.24**	58.16**	0.03	-1.06	88.61**

Panel C: Likelihood ratio tests for the World CAPM, mild segmentation APM and domestic CAPM restrictions

Restrictions	χ^2	Degree of freedom	P-value
World CAPM	4.438	3	0.218
Mild Segmentation APM	0.201	1	0.654
Domestic CAPM	0.745	2	0.689

[a] Maximum likelihood estimates for the various conditional models are obtained, using the daily Japanese (Nikkei index futures) and foreign (S&P) equity market excess returns, r_d and r_f. All excess returns are denominated by yen and are computed net of the Japanese call rate. The market value-weights for Japanese and foreign equity markets on day t are denoted by ω_d and ω_f, respectively. R^2_1 and R^2_2 denote the ratio of the explained to total variation in the excess returns associated with the Japanese and foreign equity markets. Robust t statistics are computed with quasi-maximum-likelihood methods. Significance for t statistics is denoted by * and ** at the 10 percent and 5 percent levels.

Table 16

Parameter estimates for the conditional equilibrium models of the daily expected excess returns for the U.S. and foreign equity markets [a]

Unrestricted model 1

$$r_{dt} = \alpha_d + \beta_{dw}\omega_{d,t-1}h_{dt} + \beta_{dx}(1-\omega_{d,t-1})h_{dft} + b_d' d + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{fw}\omega_{f,t-1}h_{ft} + \beta_{fx}(1-\omega_{f,t-1})h_{dft} + b_f' d + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{dft} \\ h_{dft} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

World CAPM: $\beta_{dw} = \beta_{dx} = \beta_{fw} = \beta_{fx}$

Mild segmentation APM: $\beta_{fw} = \beta_{fx}$

Unrestricted model 2

$$r_{dt} = \alpha_d + \beta_{dw}h_{dt} + \beta_{dx}h_{dft} + b_d' d + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{fw}h_{ft} + \beta_{fx}h_{dft} + b_f' d + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{dft} \\ h_{dft} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

Domestic CAPM: $\beta_{dx} = \beta_{fx} = 0$

Panel A: Period during 1980.1-1996.12

Conditional expected excess returns

Model		α_d	β_{dw}	β_{dx}	α_f	β_{fw}	β_{fx}	Log-likelihood
Unrestricted model 1	Estimate	0.0004	-2.4728	31.7357	0.0001	11.6327	-4.4004	30655.182
	Standard t-stat	1.62	-0.24	2.80**	0.44	1.93*	-0.24	R^2_d = 16.34%
	Robust t-stat	1.74*	-0.27	2.25**	0.52	2.23**	-0.22	R^2_f = 9.10%
World CAPM	Estimate	0.0003	8.8495	8.8495	0.0001	8.8495	8.8495	30652.868
	Standard t-stat	1.84*	2.20**	2.20**	0.53	2.20**	2.20**	R^2_d =16.25%
	Robust t-stat	1.71*	2.26**	2.26**	0.54	2.26**	2.26**	R^2_f = 9.14%
Mild segmentation APM	Estimate	0.0004	-1.5909	31.9794	0.0001	8.6929	8.6929	30654.939
	Standard t-stat	1.56	-0.16	2.87**	0.60	1.93*	1.93*	R^2_d = 16.35%
	Robust t-stat	1.80*	-0.17	2.46**	0.66	2.08**	2.08**	R^2_f = 9.08%
Unrestricted model 2	Estimate	0.0004	-0.5217	19.1231	-0.0001	12.6266	-12.9661	30657.246
	Standard t-stat	1.37	-0.10	2.39**	-0.37	2.71**	-1.40	R^2_d = 16.29%
	Robust t-stat	2.08**	-0.20	2.28**	-0.43	2.82**	-1.17	R^2_f = 9.16%
Domestic CAPM	Estimate	0.0002	7.1089		0.0001	6.4691		30653.313
	Standard t-stat	0.65	1.86*		0.33	2.00**		R^2_d = 16.20%
	Robust t-stat	0.73	1.88*		0.34	2.01**		R^2_f = 9.09%

Conditional covariance dynamics

		C			A				G			
		C_{11}	C_{12}	C_{22}	A_{11}	A_{21}	A_{12}	A_{22}	G_{11}	G_{21}	G_{12}	G_{22}
Unrestricted model 1	Estimate	0.0008	0.0003	0.0011	0.1664	0.0087	0.0459	0.2747	0.9812	0.0004	-0.0084	0.9519
	Standard t-stat	13.44**	1.83*	10.91**	20.35**	0.95	4.73**	25.22**	585.34**	0.13	-3.04**	254.12**
	Robust t-stat	4.27**	0.67	3.57**	8.53**	0.33	1.73*	7.00*	211.40**	0.04	-1.39	52.30**

Table 16 (continued)

Model		α_d	β_{dd}	β_{df}	α_f	β_{fd}	β_{ff}	Log-likelihood
Panel B: Period during 1980.1-1987.9								
Unrestricted model 1	Estimate	0.0000	2.5716	58.1063	0.0011	-16.6802	24.4803	13733.388
	Standard t-stat	0.05	0.12	1.65*	1.97**	-0.83	0.79	R^2_1 = 0.30%
	Robust t-stat	0.05	0.13	1.68*	2.14**	-0.94	0.59	R^2_2 = 0.05%
World CAPM	Estimate	0.0003	7.0140	7.0140	0.0004	7.0140	7.0140	13731.192
	Standard t-stat	0.72	0.78	0.78	1.04	0.78	0.78	R^2_1 = 0.02%
	Robust t-stat	0.89	1.07	1.07	1.36	1.07	1.07	R^2_2 = 0.02%
Mild segmentation APM	Estimate	0.0000	3.1829	55.1210	0.0009	-3.2121	-3.2121	13733.261
	Standard t-stat	0.06	0.15	1.56	1.88*	-0.30	-0.30	R^2_1 = 0.27%
	Robust t-stat	0.07	0.19	1.79*	1.96**	-0.33	-0.33	R^2_2 = 0.01%
Unrestricted model 2	Estimate	0.0001	0.1751	32.4001	0.0018	-26.6039	39.5532	13734.938
	Standard t-stat	0.07	0.01	1.53	2.56**	-1.77*	1.79*	R^2_1 = 0.34%
	Robust t-stat	0.08	0.01	1.29	1.97**	-1.21	1.07	R^2_2 = 0.19%
Domestic CAPM	Estimate	-0.0003	13.2776		0.0013	-8.8783		13732.841
	Standard t-stat	-0.47	1.48		2.30**	-1.05		R^2_1 = 0.15%
	Robust t-stat	-0.55	1.68*		2.21**	-1.05		R^2_2 = 0.07%
Panel C: Period during 1987.11-1996.12								
Unrestricted model 1	Estimate	0.0003	7.7489	25.7221	-0.0002	12.3427	19.2480	16834.134
	Standard t-stat	0.69	0.32	1.66*	-0.85	1.64	0.36	R^2_1 = 0.21%
	Robust t-stat	0.70	0.33	1.15	-0.98	1.78*	0.33	R^2_2 = 0.48%
World CAPM	Estimate	0.0002	13.2884	13.2884	-0.0002	13.2884	13.2884	16833.852
	Standard t-stat	1.39	2.58**	2.58**	-0.97	2.58**	2.58**	R^2_1 = 0.10%
	Robust t-stat	1.36	2.84**	2.84**	-1.04	2.84**	2.84**	R^2_2 = 0.50%
Mild segmentation APM	Estimate	0.0003	7.8217	25.3741	-0.0002	12.9298	12.9298	16834.127
	Standard t-stat	0.65	0.31	1.28	-1.06	2.89**	2.89**	R^2_1 = 0.20%
	Robust t-stat	0.70	0.33	1.66*	-0.87	2.44**	2.44**	R^2_2 = 0.48%
Unrestricted model 2	Estimate	0.0003	2.1300	17.5868	-0.0002	10.0732	0.3292	16834.458
	Standard t-stat	0.83	0.31	1.68*	-0.99	1.93*	0.02	R^2_1 = 0.20%
	Robust t-stat	0.95	0.34	1.55	-1.13	1.96**	0.02	R^2_2 = 0.51%
Domestic CAPM	Estimate	0.0002	6.3116		-0.0002	8.8260		16833.414
	Standard t-stat	0.74	1.09		-0.84	2.34**		R^2_1 = 0.07%
	Robust t-stat	0.71	0.92		-0.90	2.38**		R^2_2 = 0.37%

Panel D: Likelihood ratio tests for the World CAPM, mild segmentation APM and domestic CAPM restrictions									
Restrictions	1980.1-1996.12			1980.1-1987.9			1987.11-1996.12		
	χ^2	df	P-value	χ^2	df	P-value	χ^2	df	P-value
World CAPM	4.629	3	0.201	4.391	3	0.222	0.563	3	0.905
Mild Segmentation APM	0.487	1	0.485	0.254	1	0.614	0.014	1	0.907
Domestic CAPM	7.867	2	0.020	4.193	2	0.123	2.088	2	0.352

* Maximum likelihood estimates for the various models are obtained, using the daily U.S. and foreign equity market excess returns, r_d and r_f. All excess returns are denominated by U.S. dollars and are computed net of the U.S. t-bill rate. The market value-weights for U.S. and foreign markets on day t are denoted by ω_d and ω_f, respectively. *b* is a vector of parameters and *d* is a vector of the dummy variables which correspond to the days of market crash, October 16 19, 20 and 21 in 1987. R^2_1 and R^2_2 denote the ratio of the explained to total variation in the excess returns associated with the U.S. and foreign equity markets. Robust t statistics are computed with quasi-maximum-likelihood methods. Significance for t statistics is denoted by * and ** at the 10 percent and 5 percent levels.

The results in Panel A indicate that for the overall period, the conditional covariance of the U.S. returns with the foreign market returns has a significant positive effect on the U.S. conditional expected returns across all models that do not impose any restrictions on a coefficient for the conditional covariance. This result is consistent with that of CKS; they find a significant positive effect of the covariance on the U.S. expected returns for a variety of specifications. The results in Panel B and C indicate that the similar result holds across subperiods. Panel D reports the results from the likelihood ratio tests. The world CAPM is not rejected for the overall period and both subperiods. The mild segmentation APM is not rejected for the overall period and both subperiods. While the domestic CAPM is not rejected for two subperiods, it is rejected at the 5 percent level for the overall period. Since the world CAPM and mild segmentation APM are nested in unrestricted model 1 with a stronger restriction on the world CAPM, a failure to reject the world CAPM is likely to lead to a failure to reject the mild segmentation APM. Thus, overall results are consistent with the global integration of the U.S. market reported by CKS.

(c) Canada

Table 17 reports the parameter estimates of various models for the Canadian and foreign expected returns and the results from likelihood ratio tests for a set of restrictions. The Datastream Canada index is used to compute returns on the Canadian equity market. Returns on the foreign market are computed, using data on the Datastream world index and the market-value weights for the Canada index. All excess returns are denominated by Canadian dollars and are computed net of the Canadian Treasury bill rate.

Results in Panel A indicate that most estimates of coefficients for the conditional variance and covariance in the Canadian conditional-expected-return equation lack significance; only in unrestricted model 2, the effect of the variance is significantly positive, and the effect of the covariance is significantly negative with standard t statistics. For both subperiods, the estimates for the coefficients still lack significance, as Panel B and C indicate. Panel D reports the results from the likelihood ratio tests. The world CAPM is rejected at the 5

Table 17

Parameter estimates for the conditional equilibrium models of the daily expected excess returns for the Canadian and foreign equity markets [a]

Unrestricted model 1

$$r_{dt} = \alpha_d + \beta_{dw}\omega_{d,t-1}h_{dt} + \beta_{dc}(1-\omega_{d,t-1})h_{ct} + b_d'd + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{fw}\omega_{f,t-1}h_{ft} + \beta_{fc}(1-\omega_{f,t-1})h_{ct} + b_f'd + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

World CAPM. $\beta_{dw} = \beta_{dc} = \beta_{fw} = \beta_{fc}$

Mild segmentation APM. $\beta_{fw} = \beta_{fc}$

Unrestricted model 2

$$r_{dt} = \alpha_d + \beta_{dw}h_{dt} + \beta_{dc}h_{ct} + b_d'd + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{fw}h_{ft} + \beta_{fc}h_{ct} + b_f'd + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

Domestic CAPM $\beta_{dc} = \beta_{fc} = 0$

Panel A: Period during 1980.1-1996.12

Conditional expected excess returns

Model		α_d	β_{dw}	β_{dc}	α_f	β_{fw}	β_{fc}	Log-likelihood
Unrestricted model 1	Estimate	0.0003	51.6709	-6.9929	0.0001	8.0237	79.9795	32889.559
	Standard t-stat	2.12**	0.34	-0.79	0.30	1.50	0.36	R^2_1 = 9.98%
	Robust t-stat	1.90*	0.45	-0.90	0.27	1.26	0.36	R^2_2 = 7.89%
World CAPM	Estimate	0.0001	5.8273	5.8273	0.0002	5.8273	5.8273	32885.081
	Standard t-stat	0.87	1.33	1.33	1.05	1.33	1.33	R^2_1 = 9.95%
	Robust t-stat	0.96	1.59	1.59	1.25	1.59	1.59	R^2_2 = 7.77%
Mild segmentation APM	Estimate	0.0003	38.7993	-7.3087	0.0001	8.9900	8.9900	32889.559
	Standard t-stat	2.52**	0.28	-0.83	0.29	1.91*	1.91*	R^2_1 = 9.99%
	Robust t-stat	1.53	0.35	-0.75	0.28	1.84*	1.84*	R^2_2 = 7.88%
Unrestricted model 2	Estimate	0.0003	5.8842	-16.0504	0.0001	10.8768	-3.5778	32890.917
	Standard t-stat	2.13**	1.19	-1.75*	0.28	2.00**	-0.58	R^2_1 = 10.08%
	Robust t-stat	2.03**	1.72*	-1.90*	0.31	2.00**	-0.62	R^2_2 = 7.86%
Domestic CAPM	Estimate	0.0002	1.2023		-0.0001	11.9671		32889.179
	Standard t-stat	1.48	0.49		-0.32	3.04**		R^2_1 = 9.97%
	Robust t-stat	1.27	0.37		-0.41	3.87**		R^2_2 = 7.99%

Conditional covariance dynamics

		C			A				G			
		C_{11}	C_{12}	C_{22}	A_{11}	A_{21}	A_{12}	A_{22}	G_{11}	G_{21}	G_{12}	G_{22}
Unrestricted model 1	Estimate	0.0012	0.0004	0.0008	0.3291	-0.0282	-0.0007	0.2282	0.9279	0.0108	-0.0002	0.9649
	Standard t-stat	18.38**	4.11**	13.74**	28.29**	-2.58**	-0.06	21.05**	193.96**	2.49**	-0.04	290.20**
	Robust t-stat	3.61**	1.92*	3.11**	6.03**	-1.39	-0.02	5.38**	34.39**	1.29	-0.02	60.61**

Table 17 (continued)

Model		α_d	β_{dw}	β_{df}	α_f	β_{fw}	β_{fd}	Log-likelihood
Panel B: Period during 1980.1-1987.9								
Unrestricted model 1	Estimate	0.0000	179.1464	-9.7194	0.0003	3.1495	173.2965	14711.004
	Standard t-stat	0.13	0.84	-0.61	0.76	0.26	0.50	R^2_1 = 0.22%
	Robust t-stat	0.08	1.76*	-0.50	0.72	0.22	0.49	R^2_2 = 0.04%
World CAPM	Estimate	-0.0001	5.7206	5.7206	0.0004	5.7206	5.7206	14710.106
	Standard t-stat	-0.30	0.64	0.64	0.93	0.64	0.64	R^2_1 = 0.02%
	Robust t-stat	-0.43	1.13	1.13	1.68*	1.13	1.13	R^2_2 = 0.02%
Mild segmentation APM	Estimate	0.0001	162.6206	-10.8822	0.0003	6.6540	6.6540	14710.885
	Standard t-stat	0.34	0.81	-0.69	0.75	0.66	0.66	R^2_1 = 0.17%
	Robust t-stat	0.33	1.26	-1.34	1.12	0.98	0.98	R^2_2 = 0.02%
Unrestricted model 2	Estimate	0.0000	8.0131	-13.4941	0.0003	1.5252	7.1953	14711.643
	Standard t-stat	0.01	1.17	-0.83	0.78	0.12	0.62	R^2_1 = 0.43%
	Robust t-stat	0.01	2.14**	-0.84	0.89	0.12	0.59	R^2_2 = 0.04%
Domestic CAPM	Estimate	-0.0002	4.4736		0.0001	11.2689		14710.987
	Standard t-stat	-0.66	1.17		0.33	1.29		R^2_1 = 0.22%
	Robust t-stat	-0.62	1.09		0.30	1.14		R^2_2 = 0.06%
Panel C: Period during 1987.11-1996.12								
Unrestricted model 1	Estimate	0.0004	197.2153	-17.1884	-0.0003	16.0262	-271.9079	18085.259
	Standard t-stat	1.52	0.40	-1.30	-1.03	2.39**	-0.36	R^2_1 = 0.09%
	Robust t-stat	2.08**	0.52	-1.58	-1.23	2.38**	-0.41	R^2_2 = 0.49%
World CAPM	Estimate	0.0001	11.7266	11.7266	-0.0002	11.7266	11.7266	18081.656
	Standard t-stat	0.77	2.03**	2.03**	-0.80	2.03**	2.03**	R^2_1 = 0.06%
	Robust t-stat	0.75	2.12**	2.12**	-0.85	2.12**	2.12**	R^2_2 = 0.31%
Mild segmentation APM	Estimate	0.0004	236.4528	-16.4200	-0.0003	14.6419	14.6419	18085.196
	Standard t-stat	1.55	0.52	-1.26	-1.20	2.60**	2.60**	R^2_1 = 0.07%
	Robust t-stat	1.32	0.58	-1.78*	-1.31	2.79**	2.79**	R^2_2 = 0.50%
Unrestricted model 2	Estimate	0.0003	8.4246	-19.5607	-0.0002	16.4525	-10.0081	18085.773
	Standard t-stat	1.27	0.82	-1.53	-0.93	2.57**	-0.64	R^2_1 = 0.11%
	Robust t-stat	1.14	0.81	-2.07**	-1.30	5.50**	-0.57	R^2_2 = 0.49%
Domestic CAPM	Estimate	0.0002	3.3259		-0.0004	17.1433		18084.405
	Standard t-stat	0.85	0.44		-1.72*	3.38**		R^2_1 = 0.01%
	Robust t-stat	1.67*	0.98		-1.79*	3.26**		R^2_2 = 0.70%

Panel D: Likelihood ratio tests for the World CAPM, mild segmentation APM and domestic CAPM restrictions

Restrictions	1980.1-1996.12			1980.1-1987.9			1987.11-1996.12		
	χ^2	df	P-value	χ^2	df	P-value	χ^2	df	P-value
World CAPM	8.957	3	0.030	1.796	3	0.616	7.207	3	0.066
Mild Segmentation APM	0.104	1	0.747	0.237	1	0.626	0.127	1	0.722
Domestic CAPM	3.477	2	0.176	1.311	2	0.519	2.736	2	0.255

[a] Maximum likelihood estimates for the various conditional models are obtained, using the daily Canadian and foreign equity market excess returns, r_d and r_f. All excess returns are denominated by Canadian dollars and are computed net of the Canadian t-bill rate. The market value-weights for Canadian and foreign equity markets on day t are denoted by ω_d and ω_f, respectively. b is a vector of parameters and d is a vector of the dummy variables which correspond to the days of market crash, October 16 19, 20 and 21 in 1987. R^2_1 and R^2_2 denote the ratio of the explained to total variation in the excess returns associated with the Canadian and foreign equity markets. Robust t statistics are computed with quasi-maximum-likelihood methods. Significance for t statistics is denoted by * and ** at the 10 percent and 5 percent levels.

percent level for the overall period and at the 10 percent level for the second subperiod. Neither the mild segmentation APM nor the domestic CAPM is rejected at a conventional level for the overall period and for both subperiods. Whether the Canadian market is integrated with other markets is a controversial issue. The results from the likelihood ratio tests in this thesis seem to support the mild or complete segmentation of the Canadian market from the rest of the world.

(d) Indonesia

Table 18 reports the parameter estimates of various models for the Indonesian and foreign expected returns and the results from likelihood ratio tests for a set of restrictions. The Datastream Indonesia index is used to compute returns on the Indonesian equity market. Returns on the foreign market are computed, using data on the Datastream world index and the market-value weights for the Indonesia index. All excess returns are denominated by rupiahs and are computed net of the Indonesian interbank call rate.

When using standard t statistics, the covariance of the Indonesian market with the foreign market has a significant positive effect on the Indonesian conditional expected returns, while the variance of the Indonesian market has no effect. In contrast, when using robust t statistics, the variance has a significant positive effect on the Indonesian expected returns, while the covariance has no effect. Panel C reports the results from the likelihood ratio tests. Both the world CAPM and mild segmentation APM are rejected at the 5 percent level. However, the domestic CAPM is not rejected at the 10 percent level. These results suggest that the Indonesian equity market is completely segmented.

(e) Mexico

Table 19 reports the parameter estimates of various models for the Mexican and foreign expected returns and the results from likelihood ratio tests for a set of restrictions. The Datastream Mexico index is used to compute returns on the Mexican equity market. Returns on the foreign market are computed, using data on the Datastream world index and the

Table 18

Parameter estimates for the conditional equilibrium models of the daily expected excess returns for the Indonesian and foreign equity markets (1990.4-1996.12)[a]

Unrestricted model 1

$$r_{dt} = \alpha_d + \beta_{dd}\omega_{dt-1}h_{dt} + \beta_{df}(1-\omega_{dt-1})h_{dft} + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{ff}\omega_{ft-1}h_{ft} + \beta_{fd}(1-\omega_{ft-1})h_{dft} + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{dft} \\ h_{dft} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon'_{t-1}A$$

World CAPM: $\beta_{dd} = \beta_{df} = \beta_{ff} = \beta_{fd}$

Mild segmentation APM $\beta_{ff} = \beta_{fd}$

Unrestricted model 2

$$r_{dt} = \alpha_d + \beta_{dd}h_{dt} + \beta_{df}h_{dft} + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{ff}h_{ft} + \beta_{fd}h_{dft} + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{dft} \\ h_{dft} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon'_{t-1}A$$

Domestic CAPM $\beta_{df} = \beta_{fd} = 0$

Panel A: Conditional expected excess returns

Model		α_d	β_{dd}	β_{df}	α_f	β_{ff}	β_{fd}	Log-likelihood
Unrestricted model 1	Estimate	-0.0008	1815.6211	21.4531	-0.0002	5.1247	8248.9044	11819.145
	Standard t-stat	-2.51**	1.35	1.66*	-0.87	1.29	2.61**	R^2_1 = 0.61%
	Robust t-stat	-2.44**	2.15**	0.70	-0.82	1.27	1.56	R^2_2 = 0.19%
World CAPM	Estimate	-0.0004	4.9603	4.9603	0.0000	4.9603	4.9603	11815.028
	Standard t-stat	-1.66*	1.24	1.24	-0.22	1.24	1.24	R^2_1 = 0.01%
	Robust t-stat	-1.63	1.25	1.25	-0.23	1.25	1.25	R^2_2 = 0.12%
Mild segmentation APM	Estimate	-0.0007	1641.0611	23.1617	0.0000	3.2868	3.2868	11817.027
	Standard t-stat	-2.51**	1.34	1.81*	0.10	0.82	0.82	R^2_1 = 0.51%
	Robust t-stat	-4.08**	2.65**	0.99	0.10	0.79	0.79	R^2_2 = 0.05%
Unrestricted model 2	Estimate	-0.0005	0.9299	26.1556	-0.0001	4.2506	12.5700	11816.783
	Standard t-stat	-1.67*	0.38	2.06**	-0.43	1.08	1.59	R^2_1 = 0.30%
	Robust t-stat	-1.47	0.39	1.06	-0.64	1.70*	1.63	R^2_2 = 0.17%
Domestic CAPM	Estimate	-0.0004	1.0914		0.0000	3.8553		11814.779
	Standard t-stat	-1.54	0.51		-0.01	0.99		R^2_1 = 0.05%
	Robust t-stat	-1.25	0.41		-0.02	1.50		R^2_2 = 0.07%

Panel B: Conditional covariance dynamics

		C			A				G			
		C_{11}	C_{12}	C_{22}	A_{11}	A_{21}	A_{12}	A_{22}	G_{11}	G_{21}	G_{12}	G_{22}
Unrestricted model 1	Estimate	0.0051	0.0005	0.0000	0.6627	0.0151	-0.0055	0.1915	0.6377	-0.0161	-0.0045	0.9802
	Standard t-stat	24.24**	3.67**	0.00	27.06**	0.61	-0.46	20.71**	26.79**	-1.17	-0.52	529.53**
	Robust t-stat	6.50**	2.77**	-4.00**	12.34**	0.28	-0.47	7.66**	7.81**	-1.06	-0.48	202.68**

Panel C: Likelihood ratio tests for the World CAPM, mild segmentation APM and domestic CAPM restrictions

Restrictions	χ^2	Degree of freedom	P-value
World CAPM	8.233	3	0.041
Mild Segmentation APM	4.234	1	0.040
Domestic CAPM	4.008	2	0.135

[a] Maximum likelihood estimates for the various conditional models are obtained, using the daily Indonesian and foreign equity market excess returns, r_d and r_f. All excess returns are denominated by rupiahs and are computed net of the Indonesian call rate. The market value-weights for Indonesian and foreign equity markets on day t are denoted by ω_d and ω_f, respectively. R^2_1 and R^2_2 denote the ratio of the explained to total variation in the excess returns associated with the Indonesian and foreign equity markets. Robust t statistics are computed with quasi-maximum-likelihood methods. Significance for t statistics is denoted by * and ** at the 10 percent and 5 percent levels.

Table 19

Parameter estimates for the conditional equilibrium models of the daily expected excess returns for the Mexican and foreign equity markets (1988.1-1996.12)[a]

Unrestricted model 1

$$r_{dt} = \alpha_d + \beta_{dw}\omega_{dt-1}h_{dt} + \beta_{dc}(1-\omega_{dt-1})h_{ct} + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{fw}\omega_{ft-1}h_{ft} + \beta_{fc}(1-\omega_{ft-1})h_{ct} + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

World CAPM: $\beta_{dw} = \beta_{dc} = \beta_{fw} = \beta_{fc}$

Mild segmentation APM: $\beta_{fw} = \beta_{fc}$

Unrestricted model 2

$$r_{dt} = \alpha_d + \beta_{dw}h_{dt} + \beta_{dc}h_{ct} + \varepsilon_{dt}$$
$$r_{ft} = \alpha_f + \beta_{fw}h_{ft} + \beta_{fc}h_{ct} + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_{dt} & h_{ct} \\ h_{ct} & h_{ft} \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

Domestic CAPM: $\beta_{dc} = \beta_{fc} = 0$

Panel A: Conditional expected excess returns

Model		α_d	β_{dw}	β_{dc}	α_f	β_{fw}	β_{fc}	Log-likelihood
Unrestricted model 1	Estimate	0.0008	160.6618	-4.6966	0.0001	-3.6496	2321.8198	14693.692
	Standard t-stat	2.22**	0.42	-1.33	0.39	-2.25**	2.51**	R^2_1 = 0.12%
	Robust t-stat	2.53**	0.46	-1.21	0.36	-1.27	2.18**	R^2_2 = 4.15%
World CAPM	Estimate	0.0009	-5.0632	-5.0632	0.0004	-5.0632	-5.0632	14690.950
	Standard t-stat	3.63**	-4.63**	-4.63**	2.02**	-4.63**	-4.63**	R^2_1 = 0.11%
	Robust t-stat	4.52**	-0.88	-0.88	0.94	-0.88	-0.88	R^2_2 = 5.39%
Mild segmentation APM	Estimate	0.0009	11.2670	-3.3733	0.0004	-5.2369	-5.2369	14691.060
	Standard t-stat	2.29**	0.03	-0.87	2.08**	-4.39**	-4.39**	R^2_1 = 0.05%
	Robust t-stat	2.65**	0.03	-0.46	0.99	-0.98	-0.98	R^2_2 = 5.82%
Unrestricted model 2	Estimate	0.0000	6.4795	-2.2394	0.0000	-3.5365	16.9987	14697.240
	Standard t-stat	0.09	2.62**	-0.61	-0.02	-2.33**	3.44**	R^2_1 = 0.89%
	Robust t-stat	0.08	2.34**	-0.71	-0.02	-1.34	2.75**	R^2_2 = 4.74%
Domestic CAPM	Estimate	0.0001	4.5354		0.0004	-5.0402		14692.297
	Standard t-stat	0.36	2.06**		2.03**	-5.92**		R^2_1 = 0.38%
	Robust t-stat	0.30	1.49		1.06	-1.06		R^2_2 = 5.38%

Panel B: Conditional covariance dynamics

		C			A				G			
		C_{11}	C_{12}	C_{22}	A_{11}	A_{21}	A_{12}	A_{22}	G_{11}	G_{21}	G_{12}	G_{22}
Unrestricted model 1	Estimate	0.0028	0.0006	0.0026	0.2325	0.0445	-0.1158	0.4623	0.9491	-0.0481	0.0412	0.8474
	Standard t-stat	17.73**	1.81*	20.37**	20.76**	3.53**	-18.18**	29.01**	195.40**	-6.80**	6.90**	111.85**
	Robust t-stat	6.25**	0.80	9.58**	6.98**	1.90*	-4.98**	14.03**	71.87**	-4.16**	3.51**	44.85**

Panel C: Likelihood ratio tests for the World CAPM, mild segmentation APM and domestic CAPM restrictions

Restrictions	χ^2	Degree of freedom	P-value
World CAPM	5.482	3	0.140
Mild Segmentation APM	5.263	1	0.022
Domestic CAPM	9.886	2	0.007

[a] Maximum likelihood estimates for the various conditional models are obtained, using the daily Mexican and foreign equity market excess returns, r_d and r_f. All excess returns are denominated by Mexican pesos and are computed net of the Mexican t-bill rate. The market value-weights for Mexican and foreign equity markets on day t are denoted by ω_d and ω_f, respectively. R^2_1 and R^2_2 denote the ratio of the explained to total variation in the excess returns associated with the Mexican and foreign equity markets. Robust t statistics are computed with quasi-maximum-likelihood methods. Significance for t statistics is denoted by * and ** at the 10 percent and 5 percent levels.

Table 20

Parameter estimates for the conditional equilibrium models of the daily expected excess returns for the Taiwanese and foreign equity markets (1988.1-1996.12)[a]

Unrestricted model 1

$$r_d = \alpha_d + \beta_{dd}\omega_{d,t-1}h_d + \beta_{dc}(1-\omega_{d,t-1})h_c + \varepsilon_{dt}$$
$$r_f = \alpha_f + \beta_{ff}\omega_{f,t-1}h_f + \beta_{fc}(1-\omega_{f,t-1})h_c + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_d & h_c \\ h_c & h_f \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

World CAPM: $\beta_{dd} = \beta_{dc} = \beta_{ff} = \beta_{fc}$

Mild segmentation APM: $\beta_{ff} = \beta_{fc}$

Unrestricted model 2

$$r_d = \alpha_d + \beta_{dd}h_d + \beta_{dc}h_c + \varepsilon_{dt}$$
$$r_f = \alpha_f + \beta_{ff}h_f + \beta_{fc}h_c + \varepsilon_{ft}$$

$$\varepsilon_t \sim N(0, H_t) \text{ where } H_t = \begin{bmatrix} h_d & h_c \\ h_c & h_f \end{bmatrix} \text{ and } H_t = C'C + G'H_{t-1}G + A'\varepsilon_{t-1}\varepsilon_{t-1}'A$$

Domestic CAPM: $\beta_{dc} = \beta_{fc} = 0$

Panel A: Conditional expected excess returns

Model		α_d	β_{dd}	β_{dc}	α_f	β_{ff}	β_{fc}	Log-likelihood
Unrestricted model 1	Estimate	0.0007	-88.9870	33.2607	0.0001	2.1460	107.5439	14083.506
	Standard t-stat	1.21	-0.78	2.86**	0.48	0.45	0.30	R^2_1 = 0.49%
	Robust t-stat	1.37	-0.81	2.32**	0.56	0.49	0.19	R^2_2 =0.02%
World CAPM	Estimate	0.0004	3.9571	3.9571	0.0000	3.9571	3.9571	14081.093
	Standard t-stat	1.20	0.85	0.85	0.12	0.85	0.85	R^2_1 = 0.01%
	Robust t-stat	1.28	0.92	0.92	0.13	0.92	0.92	R^2_2 = 0.03%
Mild segmentation APM	Estimate	0.0007	-93.5953	32.8745	0.0001	2.3376	2.3376	14083.475
	Standard t-stat	1.23	-0.86	2.83**	0.46	0.49	0.49	R^2_1 = 0.48%
	Robust t-stat	1.72	-0.96	2.68**	0.52	0.52	0.52	R^2_2 = 0.01%
Unrestricted model 2	Estimate	0.0005	-0.4318	32.4529	0.0001	2.1055	0.3900	14083.212
	Standard t-stat	0.76	-0.26	2.60**	0.48	0.43	0.09	R^2_1 = 0.46%
	Robust t-stat	0.73	-0.22	1.79**	0.53	0.47	0.07	R^2_2 = 0.01%
Domestic CAPM	Estimate	0.0001	1.0786		0.0002	1.0126		14080.991
	Standard t-stat	0.22	0.75		0.61	0.22		R^2_1 = 0.04%
	Robust t-stat	0.20	0.67		0.79	0.28		R^2_2 = 2.08e-3%

Panel B: Conditional covariance dynamics

		C			A				G			
		C_{11}	C_{12}	C_{22}	A_{11}	A_{21}	A_{12}	A_{22}	G_{11}	G_{21}	G_{12}	G_{22}
Unrestricted model 1	Estimate	0.0025	0.0000	0.0003	0.2491	-0.1182	0.0116	0.1447	0.9602	0.0137	-0.0026	0.9885
	Standard t-stat	11.29**	0.40	3.90**	19.22**	-4.27**	2.87**	17.42**	250.93**	2.06**	-2.35**	785.63**
	Robust t-stat	6.17**	0.19	1.85*	13.55**	-1.54	0.95	5.37**	159.57**	1.19	-0.59	223.11**

Panel C: Likelihood ratio tests for the World CAPM, mild segmentation APM and domestic CAPM restrictions

Restrictions	χ^2	Degree of freedom	P-value
World CAPM	4.825	3	0.185
Mild Segmentation APM	0.060	1	0.806
Domestic CAPM	4.442	2	0.108

[a] Maximum likelihood estimates for the various conditional models are obtained, using the daily Taiwanese and foreign equity market excess returns, r_d and r_f. All excess returns are denominated by Taiwan dollars and are computed net of the Taiwanese swap rate. The market value-weights for Taiwanese and foreign equity markets on day t are denoted by ω_d and ω_f, respectively. R^2_1 and R^2_2 denote the ratio of the explained to total variation in the excess returns associated with the Taiwanese and foreign equity markets. Robust t statistics are computed with quasi-maximum-likelihood methods. Significance for t statistics is denoted by * and ** at the 10 percent and 5 percent levels.

market-value weights for the Mexico index. All excess returns are denominated by Mexican pesos and are computed net of the Mexican Treasury bill yield.

Results in Panel A indicate that most estimates of coefficients for the conditional variance and covariance in the Mexican conditional-expected-return equation lack significance; the variance has a significant positive effect only in unrestricted model 2 with both standard and robust t statistics and in the domestic CAPM with standard t statistics. Panel C indicates that while the world CAPM is not rejected at the 10 percent level, both the mild segmentation APM and domestic CAPM are rejected at the 5 percent level. Thus, it is suggested that Mexico is integrated. However, the estimate for the constrained parameters or aggregate relative risk aversion is significantly negative with standard t statistics. This result is inconsistent with the CAPM.

(f) Taiwan

Table 20 reports the parameter estimates of various models for the Taiwanese and foreign expected returns and the results from likelihood ratio tests for a set of restrictions. The Datastream Taiwan index is used to compute returns on the Taiwanese equity market. Returns on the foreign market are computed, using data on the Datastream world index and the market-value weights for the Taiwan index. All excess returns are denominated by Taiwan dollars and are computed net of the Taiwanese interbank swap overnight rate.

For both standard and robust t statistics, the covariance of the Taiwanese market with the foreign market has a significant positive effect on the Taiwanese conditional expected returns, but the variance of the Taiwanese market has no effect. The results from the likelihood ratio tests in Panel C indicate that none of the three models are rejected at the 10 percent level; however, p-value for the domestic CAPM is close to 10 percent. Bekaert and Harvey (1995) provide evidence that Taiwan is more integrated than segmented. Certainly, the significant covariance effect and a failure to reject the world CAPM are consistent with their result.

The results from the likelihood ratio tests for the world CAPM, the mild segmentation APM and domestic CAPM are summarized as follows:

Japan (Datastream index):

For the overall period, only the world CAPM is rejected. For the first subperiod, all three models are rejected. For the second subperiod, only the world CAPM is rejected.

Nikkei index futures:

None of the three models are rejected.

U.S.:

For the overall period, only the domestic CAPM is rejected. For both subperiods, none of the three models are rejected.

Canada:

For the overall period, only the world CAPM is rejected. For the first subperiod, none of the three models are rejected. For the second subperiod, only the world CAPM is rejected.

Indonesia:

Both the world CAPM and mild segmentation APM are rejected.

Mexico:

Both the mild segmentation APM and domestic CAPM are rejected.

Taiwan:

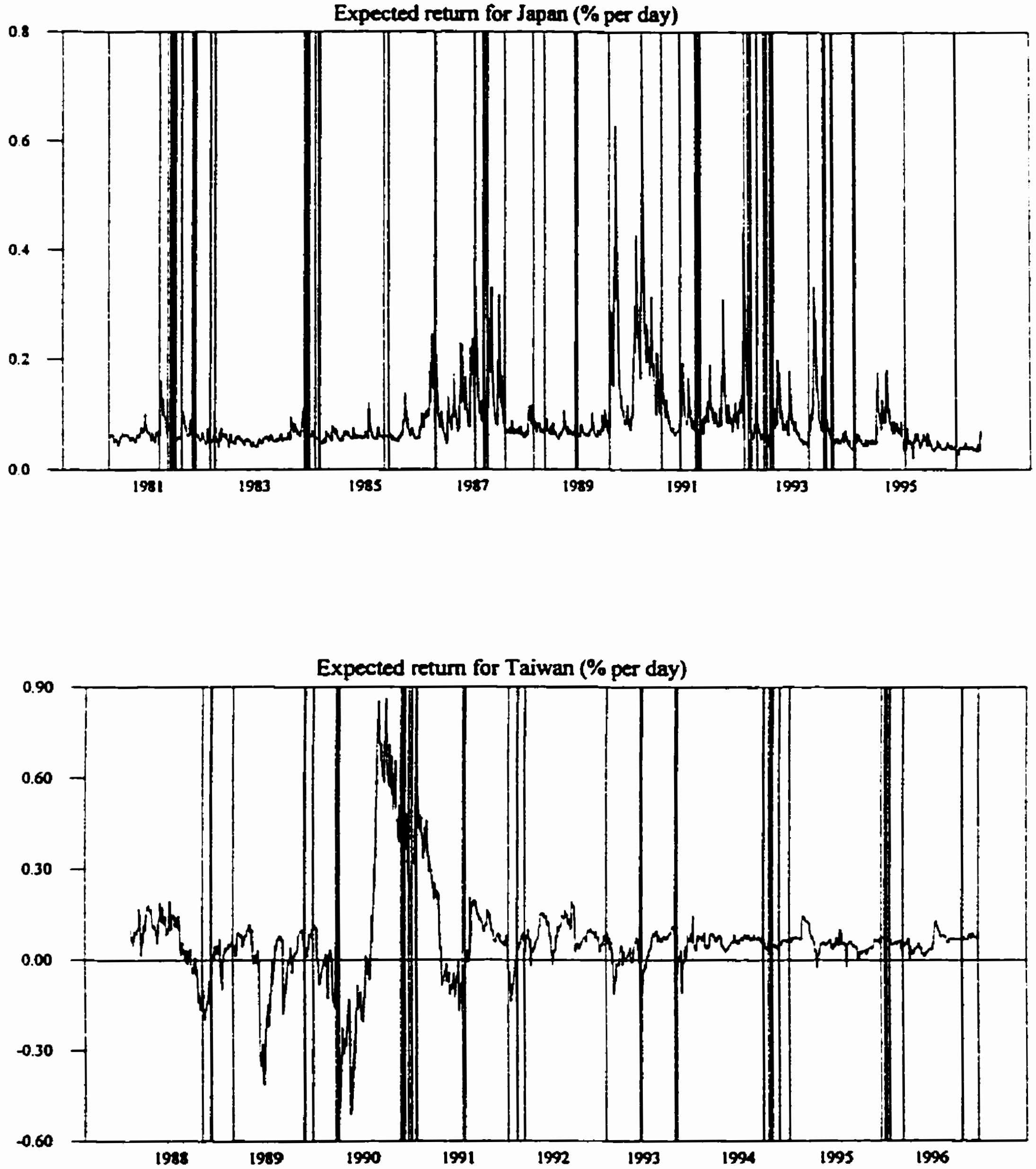
None of the three models are rejected.

How the time-varying expected returns captured by the bivariate GARCH model are related to trading rule signals may be of interest. This thesis takes as an example Japan among the developed markets and Taiwan among the emerging markets to plot expected returns and trading signals. The mild segmentation APM is used to extract expected returns, which does not constrain parameter estimates for the conditional variance and covariance in the conditional-expected-return equation of the domestic market. VMA(1, 150, 0) is used to generate signals, which seems to be appropriate for graphical presentation because of the moderate number of generated signals.

Figure 4 plots expected returns implied by the mild segmentation APM and buy signals generated by VMA (1, 150, 0) for Japan and Taiwan. Both expected returns exhibit considerable variation over time. Although no clear relationship between expected returns and trading signals can be observed in the graphs, it appears to be shown that sell signals tend to be generated when expected returns are instable. For Japan, such periods may correspond to the late 1987, the early 1990, and 1992. For Taiwan, such periods may correspond to the early 1990 and throughout 1992. Of course, this is just a casual interpretation of graphs and a more rigorous analysis is needed to make any conjecture about the relationship between expected returns and trading signals. This thesis uses the bootstrap methodologies in order to examine whether trading signals are related to time-varying expected returns in a setting of statistical testing,.

Diagnostic statistics for standardized residuals are reported in Table 21. The standardized residuals are obtained by scaling the raw residuals by the Cholesky factor of the estimated conditional covariance matrices. All mean standardized residuals are insignificantly different from zero, except for the Datastream Japan index. For the Japan index, the standardized residuals for the overall period and the second subperiod are significantly negative. This result may reflect a long-term negative drift in the Japanese market following 1989. For most of the residuals, Kolmogorov D statistics indicate significant non-normality. Thus, this thesis's use of robust t statistics is warranted. Autocorrelations of squared residuals indicate

Figure 4
Expected returns implied by the mild segmentation APM and buy signals generated by VMA(1, 150, 0) for Japan and Taiwan[a]



[a] Solid lines indicate the expected returns implied by the mild segmentation APM. Shaded regions indicate the periods for which buy signals are generated by VMA(1, 150, 0).

Table 21
Residual diagnostics for unrestricted model 1[a]

Panel A: Developed markets								
Statistic	Japan vs Foreign		Nikkei Futures vs S&P		U.S. vs Foreign		Canada vs Foreign	
	Japan	Foreign	Nikkei	S&P	U.S.	Foreign	Canada	Foreign
Period: 1980.1-1996.12								
Nobs.	4435	4435	1564	1564	4435	4435	4435	4435
Mean	-0.0535*	-0.0115	-0.0342	0.0122	-0.0231	-0.0223	-0.0054	-0.0199
Std. dev.	0.9897	1.0085	1.0005	1.0069	0.9917	1.0086	0.9902	1.0099
Kolmogorov D	0.0480*	0.0356*	0.0381	0.0434*	0.0496*	0.0255*	0.0450*	0.0291*
Series: $\hat{\varepsilon}_t$								
ρ_1	0.1433*	0.0897*	-0.0743*	-0.0171	0.1001*	0.0667*	0.2482*	0.0696*
ρ_2	0.0423*	0.0073	0.0161	0.0118	0.0170	0.0527*	0.0596*	0.0382
ρ_3	0.0097	-0.0028	0.0245	-0.0545	-0.0237	0.0131	0.0394	0.0160
Series: $\hat{\varepsilon}_t^2$								
ρ_1	0.0012	0.0293	-0.0090	0.0008	0.0122	0.0213	0.0447*	0.0676*
ρ_2	0.0244	0.0258	0.0114	-0.0002	0.0043	-0.0135	-0.0021	0.0189
ρ_3	-0.0189	0.0120	0.0004	0.0294	0.0113	0.0080	-0.0076	0.0112
Period: 1980.1-1987.9								
Nobs.	2021	2021			2021	2021	2021	2021
Mean	-0.0273	-0.0005			-0.0227	-0.0121	0.0101	-0.0186
Std. dev.	0.9919	1.0106			0.9974	1.0038	0.9883	1.0121
Kolmogorov D	0.0574*	0.0307			0.0383*	0.0212	0.0440*	0.0302
Series: $\hat{\varepsilon}_t$								
ρ_1	0.1591*	0.0831*			0.1078*	0.0713*	0.2653*	0.0679*
ρ_2	0.0458	0.0044			0.0257	0.0437	0.0537	0.0555
ρ_3	0.0120	0.0214			0.0054	0.0248	0.0269	0.0457
Series: $\hat{\varepsilon}_t^2$								
ρ_1	-0.0027	0.0757*			0.0112	0.0324	0.0229	0.0933*
ρ_2	0.0508	0.0034			-0.0276	0.0178	-0.0197	0.0363
ρ_3	-0.0351	0.0610			-0.0044	0.0340	-0.0168	0.0358
Period: 1987.11-1996.12								
Nobs.	2392	2392			2392	2392	2392	2392
Mean	-0.0632*	-0.0191			-0.0216	-0.0372	-0.0197	-0.0274
Std. dev.	0.9907	1.0119			0.9998	1.0085	0.9990	1.0072
Kolmogorov D	0.0427*	0.0424*			0.0664*	0.0366*	0.0508*	0.0279
Series: $\hat{\varepsilon}_t$								
ρ_1	0.1289*	0.1032*			0.0817*	0.0637*	0.2396*	0.0732*
ρ_2	0.0317	-0.0068			-0.0002	0.0527	0.0523	0.0347
ρ_3	0.0099	-0.0203			-0.0341	0.0009	0.0561*	-0.0149
Series: $\hat{\varepsilon}_t^2$								
ρ_1	0.0009	0.0089			0.0161	0.0032	0.0377	0.0327
ρ_2	-0.0130	0.0097			0.0032	-0.0244	-0.0053	-0.0012
ρ_3	-0.0110	0.0066			0.0036	0.0062	-0.0067	0.0008

Table 21 (continued)

Panael B: Emerging markets						
Statistic	Indonesia vs Foreign		Mexico vs Foreign		Taiwan vs Foreign	
	Indonesia	Foreign	Mexico	Foreign	Taiwan	Foreign
Nobs.	1761	1761	2346	2346	2330	2330
Mean	0.0096	-0.0082	-0.0276	0.0143	-0.0158	-0.0128
Std. dev.	0.9941	1.0079	0.9942	1.0172	0.9935	1.0066
Kolmogorov D	0.0748*	0.0464*	0.0523*	0.0596*	0.0531*	0.0455*
Series: $\hat{\varepsilon}_t$						
ρ_1	0.2166*	-0.0284	0.2562*	-0.0091	0.0451	0.0020
ρ_2	0.1417*	-0.0251	0.0280	0.0401	0.0578*	-0.0009
ρ_3	0.0511	-0.0061	0.0235	-0.0065	0.0593*	-0.0016
Series: $\hat{\varepsilon}_t^2$						
ρ_1	-0.0124	0.1445*	0.0488	0.0866	-0.0022	0.0381
ρ_2	-0.0138	-0.0021	0.0204	0.0307	0.0189	0.0485
ρ_3	-0.0036	0.0045	0.0128	-0.0015	0.0221	0.0413

[a] Diagnostics are based on the standardized residuals which are obtained by scaling raw residuals by the Cholesky factor of the estimated conditional covariance matrix. The Kolmogorov D-statistic tests the null hypothesis of normality. "*" denotes significance at the 1 % level.

that the nonlinear dependencies observed in the squared raw returns of Table 1 and 2 are mostly absorbed by the bivariate GARCH model.

For most of the residuals, significant positive autocorrelations of order one or two remain. One possibility is that the spurious autocorrelations due to nonsynchronous trading are left unexplained by the model. If this conjecture is true, an inclusion of lagged error terms in conditional-expected-return equations could remove the problem, as the model of CKS include lagged error terms. This thesis, however, does not take this approach. Since the technical trading rules tend to take advantage of positive autocorrelations in the index returns, there is the danger that the models with own lagged error terms could explain away the technical rule profits simply because of the specification having lagged errors. In other words, it would be mistakenly concluded that the equilibrium model could explain the technical rule profits even if the time-varying expected return implied by the equilibrium model did not play any major role. Thus, this thesis proceeds to bootstrap tests with estimated standardized residuals, preserving only the unconditional distributional features of the residuals.

7.4 Results from the bootstrap tests

The standard tests of trading rules explained earlier compare the conditional mean returns on the trading rules with the unconditional mean return on the buy and hold. However, if the risk of the buy and hold is different from that of the trading rules and if the expected returns are not constant over time, the use of unconditional mean return as a benchmark could be inappropriate. Instead, employing the bootstrap methodologies with equilibrium asset pricing models for the time-varying expected returns, this thesis constructs the empirical distributions of the trading rules returns, which incorporate the risk-return relation implied by the equilibrium models. Then the trading rules are evaluated by comparing the empirical distributions of the trading rule returns with the actual profits.

Three different types of equilibrium asset pricing models corresponding to complete integration, mild segmentation and complete segmentation are used for the bootstrap tests. In addition, the random walk with a drift is also used for the bootstrap tests to examine whether allowing for time-variation of expected returns makes any difference. Under each null model, price series are simulated with estimated parameters and residuals, following the procedure explained in Chapter 5. The empirical distributions of trading rule returns are obtained by applying the trading rules to each simulated price series and repeating the procedure 500 times. Specifically, the empirical distributions are constructed for the mean buy return, mean sell return and difference between the mean buy and sell returns under a given null model. The null hypothesis is rejected at the α precent significance level if the returns obtained from the actual series fall in the α precent critical region of the simulated distribution under the null model.

Table 22 - 31 report the results from the bootstrap tests. Simulated p-values defined as a fraction of 500 simulations generating a value greater than the actual conditional mean return are computed separately for individual rules in each of the three trading rule groups (i.e., VMA, FMA and TRB). To save space, however, this thesis reports simulated p-values for the averages across individual rules in each of the trading rule groups. As BLL discuss, the theoretical proof for the convergence in simulated p-values has not been provided for the GARCH model. Following BLL and Kho (1996), this thesis examines whether an increase of replication size would change bootstrap test results, taking Japan as an example case. The results for each country are explained briefly below.

(a) Japan

Table 22 reports the bootstrap test results for the period 1980 - 1996 for the Datastream Japan index. When simulating returns, dummy variables corresponding to the days of the market crash in 1987 are included for all null models, without changing the dates at which the crash occur. Since the actual trading returns are exposed to such crash, the inclusion of dummy variable for the market crash will form an appropriate base for comparisons between the actual and simulated trading rule returns. The simulated p-values, the mean of simulated distributions, and the actual conditional mean returns are reported in the rows labelled P-value, Mean, and Actual, respectively, for each trading rule group and each null model.

In Table 22, the number in the first row labelled P-value under the column labelled Buy is 0.034. This means that using the random walk, only 3.4 percent of the 500 simulations generated mean buy returns greater than the actual mean buy return for the average of the VMA rules. This result indicates that under the random walk, the simulated mean buy returns are significantly lower than the actual return at the 5 percent level. Thus, the result is interpreted as evidence that the random walk is inconsistent with the actual trading rule returns in terms of the mean buy return for the VMA rules. The number in the first row under the column labelled Sell is 0.994, which means that 99.4% of the 500 simulations generated mean sell returns greater than the actual one. In other words, only 0.6% of the 500 simulations generated mean sell returns lower than the actual return. Thus, it is indicated that the simulated sell returns under the random walk are significantly higher than the actual return. This result is interpreted as additional evidence that the random walk is inconsistent with the actual trading rule returns. Finally, the number in the first row under the column labelled Buy-Sell is 0.004, which means that only 0.4% of the 500 simulations generated buy-sell spreads (differences between the mean buy and sell returns) greater than the actual one. Thus, it is indicated that the simulated buy-sell spreads are significantly lower than the actual one, and this result is interpreted as evidence that the random walk is inconsistent with the actual trading rule returns. The overall results for the random walk indicate that the random walk is unable to explain the actual trading rule returns.

The world CAPM and domestic CAPM show only marginal improvements over the random walk. In particular, the world CAPM generates buy-sell spreads significantly lower than the actual buy-sell spreads for the VMA and FMA rules. The domestic CAPM generates sell returns significantly higher than the actual ones for the VMA and FMA rules. In contrast, the mild segmentation APM is able to explain the actual trading rule returns reasonably well for

Table 22
Bootstrap test results for technical trading rule profitability for the Datastream Japanese equity market index (1980.1-1996.12)[a]

Model	Rule	Statistic	Mean return		
			Buy	Sell	Buy-Sell
Random walk	Rule average VMA	P-value	0.034	0.994	0.004
		Mean (%)	0.0294	0.0376	-0.0083
		Actual (%)	0.0630	-0.0267	0.0896
	Rule average FMA	P-value	0.066	0.990	0.006
		Mean (%)	0.0301	0.0356	-0.0055
		Actual (%)	0.0564	-0.0166	0.0730
	Rule average TRB	P-value	0.002	0.866	0.010
		Mean (%)	0.0285	0.0600	-0.0315
		Actual (%)	0.1360	-0.0087	0.1446
World CAPM	Rule average VMA	P-value	0.050	0.930	0.010
		Mean (%)	0.0203	0.0196	0.0007
		Actual (%)	0.0630	-0.0267	0.0896
	Rule average FMA	P-value	0.056	0.876	0.016
		Mean (%)	0.0198	0.0201	-0.0003
		Actual (%)	0.0564	-0.0166	0.0730
	Rule average TRB	P-value	0.042	0.662	0.092
		Mean (%)	0.1606	0.0343	0.1263
		Actual (%)	0.1360	-0.0087	0.1446
Mild segm. APM	Rule average VMA	P-value	0.168	0.800	0.074
		Mean (%)	0.0437	0.0158	0.0279
		Actual (%)	0.0630	-0.0267	0.0896
	Rule average FMA	P-value	0.176	0.730	0.092
		Mean (%)	0.0423	0.0161	0.0262
		Actual (%)	0.0564	-0.0166	0.0730
	Rule average TRB	P-value	0.148	0.584	0.148
		Mean (%)	0.0805	0.0342	0.0461
		Actual (%)	0.1360	-0.0087	0.1446
Domestic CAPM	Rule average VMA	P-value	0.206	0.998	0.040
		Mean (%)	0.0573	0.0469	0.0104
		Actual (%)	0.0630	-0.0267	0.0896
	Rule average FMA	P-value	0.258	0.996	0.054
		Mean (%)	0.0563	0.0455	0.0108
		Actual (%)	0.0564	-0.0166	0.0730
	Rule average TRB	P-value	0.200	0.898	0.106
		Mean (%)	0.1295	0.1071	0.0224
		Actual (%)	0.1360	-0.0087	0.1446

[a] The return series are simulated using estimated parameters and standardized residuals for each null model. Numbers in the rows labeled P-value are the fraction of the 500 simulations generating conditional mean returns (the mean buy return, mean sell return, and buy-sell spread) greater than those from the actual series reported before. Mean refers to the mean of the simulated distributions. Actual refers to the actual mean returns.

Table 23
Bootstrap test results using 1000 simulations and results by subperiod for the Datastream Japanese equity market index[a]

Panel A: 1000 simulations (1980.1-1996.12)					
Model	Rule		Mean return		
			Buy	Sell	Buy-Sell
Random walk	Rule average VMA	P-value	0.044	0.997	0.002
	Rule average FMA	P-value	0.078	0.991	0.005
	Rule average TRB	P-value	0.001	0.870	0.005
World CAPM	Rule average VMA	P-value	0.053	0.941	0.016
	Rule average FMA	P-value	0.063	0.884	0.024
	Rule average TRB	P-value	0.054	0.686	0.094
Mild segm. APM	Rule average VMA	P-value	0.157	0.827	0.060
	Rule average FMA	P-value	0.167	0.758	0.073
	Rule average TRB	P-value	0.144	0.597	0.134
Domestic CAPM	Rule average VMA	P-value	0.208	0.998	0.044
	Rule average FMA	P-value	0.269	0.996	0.056
	Rule average TRB	P-value	0.189	0.893	0.105
Panel B: Subperiod 1980.1-1987.9 with 500 simulations					
Random walk	Rule average VMA	P-value	0.256	0.740	0.166
	Rule average FMA	P-value	0.328	0.666	0.234
	Rule average TRB	P-value	0.000	0.264	0.438
World CAPM	Rule average VMA	P-value	0.256	0.730	0.184
	Rule average FMA	P-value	0.294	0.664	0.232
	Rule average TRB	P-value	0.094	0.460	0.398
Mild segm. APM	Rule average VMA	P-value	0.478	0.766	0.220
	Rule average FMA	P-value	0.510	0.700	0.300
	Rule average TRB	P-value	0.310	0.534	0.408
Domestic CAPM	Rule average VMA	P-value	0.502	0.822	0.208
	Rule average FMA	P-value	0.536	0.756	0.282
	Rule average TRB	P-value	0.358	0.552	0.432
Panel C: Subperiod 1987.11-1996.12 with 500 simulations					
Random walk	Rule average VMA	P-value	0.102	0.964	0.024
	Rule average FMA	P-value	0.182	0.900	0.060
	Rule average TRB	P-value	0.078	0.876	0.046
World CAPM	Rule average VMA	P-value	0.188	0.868	0.040
	Rule average FMA	P-value	0.256	0.744	0.096
	Rule average TRB	P-value	0.272	0.804	0.170
Mild segm. APM	Rule average VMA	P-value	0.542	0.812	0.212
	Rule average FMA	P-value	0.594	0.726	0.314
	Rule average TRB	P-value	0.602	0.784	0.288
Domestic CAPM	Rule average VMA	P-value	0.138	0.954	0.030
	Rule average FMA	P-value	0.230	0.902	0.076
	Rule average TRB	P-value	0.232	0.902	0.106

[a] The return series are simulated using estimated parameters and standardized residuals for each null model. Numbers in the rows labeled P-value are the fraction of the 1000 simulations (500 simulations for Panel B and C) generating conditional mean returns (the mean buy return, mean sell return, and buy-sell spread) greater than those from the actual series reported before.

all out of 9 mean returns (the mean buy return, mean sell return, and buy-sell spread times three trading rule groups). The mild segmentation APM generates buy (sell) returns insignificantly lower (higher) than the actual buy (sell) returns at the 5 percent level for all the trading rule groups; consequently, the simulated buy-sell spreads are insignificantly different from the actual spreads at the 5 percent level for all three trading rule groups. The mean of the simulated buy-sell spreads ranges from 31 percent to 36 percent of the actual spreads.

Panel A of table 23 reports the bootstrap test results using 1000 simulations. Simulated p-values closely resemble those reported in Table 22, and inferences do not change across 500 and 1000 simulations. Panel B and C of table 23 report the results for two subperiods without October 1987, respectively. The tests based on subperiods without October 1987 are free from the effects of dummy variables for the market crash. Further, the second subperiod becomes a base for comparison between the advanced and emerging markets because the sample period for the emerging markets starts in 1988. For the first subperiod, all null models seem to be consistent with the actual trading rule returns, except that under the random walk, the simulated buy returns are significantly lower than the actual return for the TRB at the 1 percent level. Given relatively weak trading rule results for the first subperiod in Table 4, this result may not be surprising. For the second subperiod, however, the bootstrap tests show much stronger power. That is, among all null models, the mild segmentation APM performs best and is able to replicate the actual trading rule returns reasonably well for all out of the 9 mean returns at the 5 percent level.

Table 24 reports the results for the Nikkei index futures. All null models are consistent with the actual mean returns for all trading rule groups. There seems to be no large difference in performance among the null models. Thus, the bootstrap tests lack power. This result is not surprising because the standard tests do not detect any significant forecast power for the Nikkei index futures, as is reported earlier.

Table 24
Bootstrap test results for technical trading rule profitability for the Nikkei index futures (1990.12-1996.12)[a]

Model	Rule	Statistic	Mean return		
			Buy	Sell	Buy-Sell
Random walk	Rule average VMA	P-value	0.320	0.578	0.272
		Mean (%)	-0.0388	-0.0189	-0.0199
		Actual (%)	-0.0062	-0.0317	0.0255
	Rule average FMA	P-value	0.338	0.584	0.258
		Mean (%)	-0.0376	-0.0197	-0.0179
		Actual (%)	-0.0054	-0.0343	0.0289
	Rule average TRB	P-value	0.324	0.436	0.388
		Mean (%)	-0.0004	-0.0002	-0.0002
		Actual (%)	0.0278	-0.0097	0.0375
World CAPM	Rule average VMA	P-value	0.322	0.454	0.340
		Mean (%)	-0.0450	-0.0345	-0.0105
		Actual (%)	-0.0062	-0.0317	0.0255
	Rule average FMA	P-value	0.298	0.464	0.324
		Mean (%)	-0.0432	-0.0343	-0.0089
		Actual (%)	-0.0054	-0.0343	0.0289
	Rule average TRB	P-value	0.320	0.408	0.380
		Mean (%)	-0.0389	-0.0203	-0.0184
		Actual (%)	0.0278	-0.0097	0.0375
Mild segm. APM	Rule average VMA	P-value	0.390	0.468	0.394
		Mean (%)	-0.026	-0.031	0.005
		Actual (%)	-0.0062	-0.0317	0.0255
	Rule average FMA	P-value	0.362	0.502	0.362
		Mean (%)	-0.0269	-0.0308	0.0039
		Actual (%)	-0.0054	-0.0343	0.0289
	Rule average TRB	P-value	0.400	0.424	0.462
		Mean (%)	-0.0064	-0.0190	0.0124
		Actual (%)	0.0278	-0.0097	0.0375
Domestic CAPM	Rule average VMA	P-value	0.360	0.442	0.354
		Mean (%)	-0.0367	-0.0322	-0.0044
		Actual (%)	-0.0062	-0.0317	0.0255
	Rule average FMA	P-value	0.320	0.486	0.310
		Mean (%)	-0.0361	-0.0318	-0.0043
		Actual (%)	-0.0054	-0.0343	0.0289
	Rule average TRB	P-value	0.336	0.426	0.394
		Mean (%)	-0.0304	-0.0234	-0.0069
		Actual (%)	0.0278	-0.0097	0.0375

[a] The return series are simulated using estimated parameters and standardized residuals for each null model. Numbers in the rows labeled P-value are the fraction of the 500 simulations generating conditional mean returns (the mean buy return, mean sell return, and buy-sell spread) greater than those from the actual series reported before. Mean refers to the mean of the simulated distributions. Actual refers to the actual mean returns.

(b) U.S.

Table 25 reports the bootstrap test results for the period 1980 - 1996 for the Datastream U.S. index. When simulating returns, dummy variables corresponding to the days of the market crash in 1987 are included in all null models. Table 26 reports the results by subperiod for the Datastream U.S. index.

All null models are consistent with the actual mean returns for all trading rule groups over the overall period. The similar result holds across both subperiods. This is understandable because the standard tests do not detect any significant forecast power for the Datastream U.S. index. Thus, bootstrap tests further confirm that the technical trading rules examined by BLL are not profitable for the U.S. market at least during the recent period.

(c) Canada

Table 27 reports the bootstrap test results for the period 1980 - 1996 for the Datastream Canada index. When simulating returns, dummy variables corresponding to the days of the market crash in 1987 are included in all null models.

The random walk generates returns significantly different from the actual returns at the 5 percent level for 8 out of 9 mean returns. Further, the world CAPM, mild segmentation APM and domestic CAPM show only marginal improvements over the random walk. All three equilibrium models generate buy (sell) returns significantly lower (higher) than the actual trading rule returns at the 5 percent level for the VMA; consequently, all three models generate buy-sell spreads significantly lower than the actual spread at the 5 percent level for the VMA. Further, all three equilibrium models generate buy returns significantly lower than the actual trading rule returns at the 5 percent level for the TRB. Table 28 reports the results by subperiod for the Datastream Canada index. For the first subperiod, all null models generate buy-sell spreads significantly lower than the actual buy-sell spreads at the 1 percent level for the VMA and FMA rules. For the second subperiod, the random walk generate returns significantly different from the actual spreads at the 5 percent level for the VMA and

Table 25
Bootstrap test results for technical trading rule profitability for the Datastream U.S. equity market index (1980.1-1996.12)[a]

Model	Rule	Statistic	Mean return		
			Buy	Sell	Buy-Sell
Random walk	Rule average VMA	P-value	0.416	0.806	0.188
		Mean (%)	0.0564	0.0671	-0.0107
		Actual (%)	0.0603	0.0425	0.0179
	Rule average FMA	P-value	0.668	0.272	0.762
		Mean (%)	0.0571	0.0618	-0.0047
		Actual (%)	0.0505	0.0754	-0.0249
	Rule average TRB	P-value	0.520	0.216	0.768
		Mean (%)	0.0575	0.1437	-0.0862
		Actual (%)	0.0575	0.2173	-0.1598
World CAPM	Rule average VMA	P-value	0.604	0.816	0.220
		Mean (%)	0.0644	0.0762	-0.0117
		Actual (%)	0.0603	0.0425	0.0179
	Rule average FMA	P-value	0.798	0.424	0.692
		Mean (%)	0.0643	0.0732	-0.0089
		Actual (%)	0.0505	0.0754	-0.0249
	Rule average TRB	P-value	0.654	0.200	0.828
		Mean (%)	0.0694	0.1309	-0.0614
		Actual (%)	0.0575	0.2173	-0.1598
Mild segm. APM	Rule average VMA	P-value	0.352	0.632	0.310
		Mean (%)	0.0559	0.0549	0.0010
		Actual (%)	0.0603	0.0425	0.0179
	Rule average FMA	P-value	0.616	0.210	0.798
		Mean (%)	0.0554	0.0538	0.0017
		Actual (%)	0.0505	0.0754	-0.0249
	Rule average TRB	P-value	0.570	0.090	0.916
		Mean (%)	0.0677	0.0821	-0.0145
		Actual (%)	0.0575	0.2173	-0.1598
Domestic CAPM	Rule average VMA	P-value	0.358	0.786	0.190
		Mean (%)	0.0568	0.0673	-0.0105
		Actual (%)	0.0603	0.0425	0.0179
	Rule average FMA	P-value	0.644	0.342	0.728
		Mean (%)	0.0563	0.0662	-0.0099
		Actual (%)	0.0505	0.0754	-0.0249
	Rule average TRB	P-value	0.564	0.128	0.860
		Mean (%)	0.0623	0.1054	-0.0430
		Actual (%)	0.0575	0.2173	-0.1598

[a] The return series are simulated using estimated parameters and standardized residuals for each null model. Numbers in the rows labeled P-value are the fraction of the 500 simulations generating conditional mean returns (the mean buy return, mean sell return, and buy-sell spread) greater than those from the actual series reported before. Mean refers to the mean of the simulated distributions. Actual refers to the actual mean returns.

Table 26
Bootstrap test results by subperiod for the Datastream U.S. equity market index[a]

Model	Rule		Mean return Buy	Mean return Sell	Mean return Buy-Sell
Panel A: Subperiod 1980.1-1987.9					
Random walk	Rule average VMA	P-value	0.378	0.858	0.110
	Rule average FMA	P-value	0.490	0.710	0.262
	Rule average TRB	P-value	0.410	0.164	0.814
World CAPM	Rule average VMA	P-value	0.320	0.826	0.118
	Rule average FMA	P-value	0.448	0.638	0.268
	Rule average TRB	P-value	0.428	0.162	0.804
Mild segm. APM	Rule average VMA	P-value	0.382	0.904	0.104
	Rule average FMA	P-value	0.518	0.754	0.250
	Rule average TRB	P-value	0.560	0.234	0.766
Domestic CAPM	Rule average VMA	P-value	0.404	0.854	0.124
	Rule average FMA	P-value	0.502	0.702	0.288
	Rule average TRB	P-value	0.534	0.202	0.790
Panel B: Subperiod 1987.11-1996.12					
Random walk	Rule average VMA	P-value	0.502	0.300	0.652
	Rule average FMA	P-value	0.604	0.152	0.882
	Rule average TRB	P-value	0.654	0.120	0.870
World CAPM	Rule average VMA	P-value	0.628	0.468	0.584
	Rule average FMA	P-value	0.730	0.268	0.782
	Rule average TRB	P-value	0.740	0.216	0.834
Mild segm. APM	Rule average VMA	P-value	0.634	0.376	0.674
	Rule average FMA	P-value	0.724	0.252	0.822
	Rule average TRB	P-value	0.776	0.214	0.850
Domestic CAPM	Rule average VMA	P-value	0.516	0.418	0.534
	Rule average FMA	P-value	0.620	0.250	0.770
	Rule average TRB	P-value	0.624	0.180	0.830

[a] The return series are simulated using estimated parameters and standardized residuals for each null model. Numbers in the rows labeled P-value are the fraction of the 500 simulations generating conditional mean returns (the mean buy return, mean sell return, and buy-sell spread) greater than those from the actual series reported before.

Table 27
Bootstrap test results for technical trading rule profitability for the Datastream Canadian equity market index (1980.1-1996.12)[a]

Model	Rule	Statistic	Mean return		
			Buy	Sell	Buy-Sell
Random walk	Rule average VMA	P-value	0.010	0.998	0.002
		Mean (%)	0.0388	0.0441	-0.0053
		Actual (%)	0.0640	-0.0191	0.0831
	Rule average FMA	P-value	0.174	0.958	0.036
		Mean (%)	0.0388	0.0431	-0.0043
		Actual (%)	0.0495	0.0122	0.0373
	Rule average TRB	P-value	0.002	0.972	0.010
		Mean (%)	0.0402	0.0681	-0.0279
		Actual (%)	0.1101	-0.0802	0.1903
World CAPM	Rule average VMA	P-value	0.022	0.992	0.000
		Mean (%)	0.0401	0.0391	0.0010
		Actual (%)	0.0640	-0.0191	0.0831
	Rule average FMA	P-value	0.168	0.902	0.064
		Mean (%)	0.0392	0.0408	-0.0016
		Actual (%)	0.0495	0.0122	0.0373
	Rule average TRB	P-value	0.012	0.910	0.042
		Mean (%)	0.0428	0.0386	0.0042
		Actual (%)	0.1101	-0.0802	0.1903
Mild segm. APM	Rule average VMA	P-value	0.022	0.982	0.004
		Mean (%)	0.0391	0.0328	0.0063
		Actual (%)	0.0640	-0.0191	0.0831
	Rule average FMA	P-value	0.168	0.856	0.094
		Mean (%)	0.0379	0.0349	0.0031
		Actual (%)	0.0495	0.0122	0.0373
	Rule average TRB	P-value	0.012	0.890	0.034
		Mean (%)	0.0370	0.0244	0.0126
		Actual (%)	0.1101	-0.0802	0.1903
Domestic CAPM	Rule average VMA	P-value	0.020	0.990	0.002
		Mean (%)	0.0409	0.0381	0.0028
		Actual (%)	0.0640	-0.0191	0.0831
	Rule average FMA	P-value	0.220	0.900	0.066
		Mean (%)	0.0399	0.0400	-0.0001
		Actual (%)	0.0495	0.0122	0.0373
	Rule average TRB	P-value	0.014	0.876	0.054
		Mean (%)	0.0443	0.0354	0.0089
		Actual (%)	0.1101	-0.0802	0.1903

[a] The return series are simulated using estimated parameters and standardized residuals for each null model. Numbers in the rows labeled P-value are the fraction of the 500 simulations generating conditional mean returns (the mean buy return, mean sell return, and buy-sell spread) greater than those from the actual series reported before. Mean refers to the mean of the simulated distributions. Actual refers to the actual mean returns.

Table 28
Bootstrap test results by subperiod for the Datastream Canadian equity market index[a]

Model	Rule		Mean return Buy	Mean return Sell	Mean return Buy-Sell
Panel A: Subperiod 1980.1-1987.9					
Random walk	Rule average VMA	P-value	0.074	1.000	0.000
	Rule average FMA	P-value	0.166	0.996	0.006
	Rule average TRB	P-value	0.008	0.854	0.026
World CAPM	Rule average VMA	P-value	0.034	0.996	0.004
	Rule average FMA	P-value	0.100	0.990	0.014
	Rule average TRB	P-value	0.034	0.818	0.074
Mild segm. APM	Rule average VMA	P-value	0.074	0.986	0.002
	Rule average FMA	P-value	0.122	0.944	0.016
	Rule average TRB	P-value	0.076	0.742	0.102
Domestic CAPM	Rule average VMA	P-value	0.068	0.998	0.002
	Rule average FMA	P-value	0.150	0.994	0.006
	Rule average TRB	P-value	0.078	0.884	0.046
Panel B: Subperiod 1987.11-1996.12					
Random walk	Rule average VMA	P-value	0.128	0.926	0.024
	Rule average FMA	P-value	0.370	0.708	0.206
	Rule average TRB	P-value	0.166	0.970	0.020
World CAPM	Rule average VMA	P-value	0.078	0.822	0.062
	Rule average FMA	P-value	0.276	0.636	0.254
	Rule average TRB	P-value	0.224	0.932	0.046
Mild segm. APM	Rule average VMA	P-value	0.132	0.702	0.128
	Rule average FMA	P-value	0.344	0.464	0.394
	Rule average TRB	P-value	0.224	0.910	0.070
Domestic CAPM	Rule average VMA	P-value	0.088	0.840	0.066
	Rule average FMA	P-value	0.286	0.636	0.256
	Rule average TRB	P-value	0.188	0.928	0.042

[a] The return series are simulated using estimated parameters and standardized residuals for each null model. Numbers in the rows labeled P-value are the fraction of the 500 simulations generating conditional mean returns (the mean buy return, mean sell return, and buy-sell spread) greater than those from the actual series reported before.

TRB. The world CAPM and domestic CAPM show relatively marginal improvements over the random walk. In contrast, the mild segmentation APM performs best and seems to be able to explain the actual trading rule returns reasonably well for all out of 9 mean returns. The mild segmentation APM generates buy (sell) returns insignificantly lower (higher) than the actual buy (sell) returns at the 5 percent level for all the trading rule groups; consequently, the simulated buy-sell spreads are insignificantly different from the actual spreads at the 5 percent level for all trading rule groups.

(d) Indonesia

Table 29 reports the bootstrap test results for the period 1990.4 - 1996.12 for the Datastream Indonesia index.

The results indicate that none of the null models seem to be consistent with the actual trading rule returns for the Indonesia index. In particular, the results for the TRB rules are very strong; for all null models and all mean returns, the simulated returns are significantly different from the actual trading rule returns at the 5 percent level.

(e) Mexico

Table 30 reports the bootstrap test results for the period 1988.1 - 1996.12 for the Datastream Mexico index.

For the VMA rules, some null models seem to be able to replicate the actual trading returns moderately. For the FMA rules, all the null models seem to be consistent with the actual trading rule returns. For the TRB rules, however, all null models generate trading rule returns significantly different from the actual returns at the 5 percent level in terms of the mean buy return, mean sell return, and buy-sell spread.

(f) Taiwan

Table 31 reports the bootstrap test results for the period 1988.1 - 1996.12 for the Datastream

Table 29
Bootstrap test results for technical trading rule profitability for the Datastream Indonesian equity market index (1990.4-1996.12)[a]

Model	Rule	Statistic	Mean return		
			Buy	Sell	Buy-Sell
Random walk	Rule average VMA	P-value	0.000	0.894	0.006
		Mean (%)	-0.0029	0.0121	-0.0151
		Actual (%)	0.0988	-0.0376	0.1363
	Rule average FMA	P-value	0.022	0.670	0.024
		Mean (%)	-0.0024	0.0119	-0.0143
		Actual (%)	0.0779	-0.0060	0.0839
	Rule average TRB	P-value	0.000	0.998	0.000
		Mean (%)	-0.0044	0.0141	-0.0184
		Actual (%)	0.2736	-0.2190	0.4926
World CAPM	Rule average VMA	P-value	0.010	0.894	0.010
		Mean (%)	0.0028	0.0199	-0.0171
		Actual (%)	0.0988	-0.0376	0.1363
	Rule average FMA	P-value	0.030	0.690	0.054
		Mean (%)	0.0049	0.0172	-0.0123
		Actual (%)	0.0779	-0.0060	0.0839
	Rule average TRB	P-value	0.012	0.952	0.002
		Mean (%)	-0.0068	0.0320	-0.0389
		Actual (%)	0.2736	-0.2190	0.4926
Mild segm. APM	Rule average VMA	P-value	0.014	0.716	0.030
		Mean (%)	0.0504	-0.0133	0.0637
		Actual (%)	0.0988	-0.0376	0.1363
	Rule average FMA	P-value	0.024	0.460	0.078
		Mean (%)	0.0504	-0.0133	0.0637
		Actual (%)	0.0779	-0.0060	0.0839
	Rule average TRB	P-value	0.004	0.992	0.004
		Mean (%)	0.0480	-0.0128	0.0607
		Actual (%)	0.2736	-0.2190	0.4926
Domestic CAPM	Rule average VMA	P-value	0.022	0.934	0.012
		Mean (%)	0.0118	0.0315	-0.0197
		Actual (%)	0.0988	-0.0376	0.1363
	Rule average FMA	P-value	0.062	0.778	0.046
		Mean (%)	0.0135	0.0281	-0.0146
		Actual (%)	0.0779	-0.0060	0.0839
	Rule average TRB	P-value	0.024	0.986	0.010
		Mean (%)	0.0283	0.0667	-0.0384
		Actual (%)	0.2736	-0.2190	0.4926

[a] The return series are simulated using estimated parameters and standardized residuals for each null model. Numbers in the rows labeled P-value are the fraction of the 500 simulations generating conditional mean returns (the mean buy return, mean sell return, and buy-sell spread) greater than those from the actual series reported before. Mean refers to the mean of the simulated distributions. Actual refers to the actual mean returns.

Table 30
Bootstrap test results for technical trading rule profitability for the Datastream Mexican equity market index (1988.1-1996.12)[a]

Model	Rule	Statistic	Mean return		
			Buy	Sell	Buy-Sell
Random walk	Rule average VMA	P-value	0.372	0.954	0.072
		Mean (%)	0.1413	0.1788	-0.0375
		Actual (%)	0.1517	0.0496	0.1021
	Rule average FMA	P-value	0.492	0.918	0.114
		Mean (%)	0.1415	0.1695	-0.0280
		Actual (%)	0.1420	0.0715	0.0706
	Rule average TRB	P-value	0.002	0.988	0.006
		Mean (%)	0.1400	0.1868	-0.0470
		Actual (%)	0.3068	-0.2123	0.5191
World CAPM	Rule average VMA	P-value	0.190	0.906	0.058
		Mean (%)	0.1249	0.1581	-0.0332
		Actual (%)	0.1517	0.0496	0.1021
	Rule average FMA	P-value	0.274	0.834	0.116
		Mean (%)	0.1243	0.1519	-0.0276
		Actual (%)	0.1420	0.0715	0.0706
	Rule average TRB	P-value	0.002	0.974	0.008
		Mean (%)	0.1293	0.1986	-0.0691
		Actual (%)	0.3068	-0.2123	0.5191
Mild segm. APM	Rule average VMA	P-value	0.194	0.892	0.060
		Mean (%)	0.1314	0.1646	-0.0333
		Actual (%)	0.1517	0.0496	0.1021
	Rule average FMA	P-value	0.272	0.814	0.132
		Mean (%)	0.1310	0.1557	-0.0247
		Actual (%)	0.1420	0.0715	0.0706
	Rule average TRB	P-value	0.008	0.974	0.010
		Mean (%)	0.1394	0.1702	-0.0308
		Actual (%)	0.3068	-0.2123	0.5191
Domestic CAPM	Rule average VMA	P-value	0.248	0.920	0.056
		Mean (%)	0.1287	0.1695	-0.0408
		Actual (%)	0.1517	0.0496	0.1021
	Rule average FMA	P-value	0.340	0.876	0.100
		Mean (%)	0.1285	0.1609	-0.0324
		Actual (%)	0.1420	0.0715	0.0706
	Rule average TRB	P-value	0.002	0.980	0.008
		Mean (%)	0.1339	0.1965	-0.0624
		Actual (%)	0.3068	-0.2123	0.5191

[a] The return series are simulated using estimated parameters and standardized residuals for each null model. Numbers in the rows labeled P-value are the fraction of the 500 simulations generating conditional mean returns (the mean buy return, mean sell return, and buy-sell spread) greater than those from the actual series reported before. Mean refers to the mean of the simulated distributions. Actual refers to the actual mean returns.

Table 31
Bootstrap tests for technical trading rule profitability for the Datastream Taiwanese equity market index (1988.1-1996.12)[a]

Model	Rule	Statistic	Mean return		
			Buy	Sell	Buy-Sell
Random walk	Rule average VMA	P-value	0.200	0.952	0.040
		Mean (%)	0.0225	0.0461	-0.0236
		Actual (%)	0.0776	-0.0629	0.1406
	Rule average FMA	P-value	0.254	0.960	0.052
		Mean (%)	0.0234	0.0441	-0.0207
		Actual (%)	0.0668	-0.0565	0.1233
	Rule average TRB	P-value	0.056	0.986	0.006
		Mean (%)	0.0199	0.0502	-0.0302
		Actual (%)	0.1950	-0.2084	0.4034
World CAPM	Rule average VMA	P-value	0.164	0.938	0.038
		Mean (%)	0.0213	0.0365	-0.0152
		Actual (%)	0.0776	-0.0629	0.1406
	Rule average FMA	P-value	0.210	0.928	0.046
		Mean (%)	0.0218	0.0361	-0.0142
		Actual (%)	0.0668	-0.0565	0.1233
	Rule average TRB	P-value	0.040	0.954	0.014
		Mean (%)	0.0135	0.0359	-0.0224
		Actual (%)	0.1950	-0.2084	0.4034
Mild segm. APM	Rule average VMA	P-value	0.306	0.776	0.166
		Mean (%)	0.0496	0.0006	0.0491
		Actual (%)	0.0776	-0.0629	0.1406
	Rule average FMA	P-value	0.372	0.770	0.204
		Mean (%)	0.0468	0.0038	0.0430
		Actual (%)	0.0668	-0.0565	0.1233
	Rule average TRB	P-value	0.072	0.842	0.080
		Mean (%)	0.0540	-0.0351	0.0891
		Actual (%)	0.1950	-0.2084	0.4034
Domestic CAPM	Rule average VMA	P-value	0.214	0.960	0.022
		Mean (%)	0.0341	0.0538	-0.0197
		Actual (%)	0.0776	-0.0629	0.1406
	Rule average FMA	P-value	0.266	0.952	0.038
		Mean (%)	0.0337	0.0531	-0.0194
		Actual (%)	0.0668	-0.0565	0.1233
	Rule average TRB	P-value	0.062	0.966	0.014
		Mean (%)	0.0255	0.0626	-0.0371
		Actual (%)	0.1950	-0.2084	0.4034

[a] The return series are simulated using estimated parameters and standardized residuals for each null model. Numbers in the rows labeled P-value are the fraction of the 500 simulations generating conditional mean returns (the mean buy return, mean sell return, and buy-sell spread) greater than those from the actual series reported before. Mean refers to the mean of the simulated distributions. Actual refers to the actual mean returns.

Taiwan index.

The random walk generates buy-sell spreads significantly lower than the actual buy-sell spreads for the VMA and TRB. The results for the world CAPM and domestic CAPM are similar to those of the random walk. In contrast, the mild segmentation APM performs best, and the simulated buy (sell) returns are insignificantly lower (higher) than the actual buy (sell) returns at the 5 percent level for all trading rule groups; consequently, the simulated buy-sell spreads are insignificantly different from the actual spreads at the 5 percent level for all three trading rule groups. For the mild segmentation APM, the mean of the simulated buy-sell spreads ranges from 22 percent to 35 percent of the actual buy-sell spreads.

The bootstrap test results are summarized as follows:

Japan (Datastream index):

For the overall period, the mild segmentation APM performs best to replicate the actual trading rule returns. Assuming the 5 percent significance level, the mild segmentation APM is consistent with all actual trading rule returns. For the first subperiod, all equilibrium models are consistent with the actual trading rule returns. For the second subperiod, only the mild segmentation APM is consistent with the actual trading rule returns at the 5 percent significance level.

Nikkei index futures:

All null models are consistent with the actual trading rule returns at the 5 percent significant level.

U.S.:

All null models are consistent with the actual trading rule returns for the overall period and across both subperiods at the 5 percent significance level.

Canada:

Assuming the 5 percent significance level, none of the null models are completely consistent with the actual trading rule returns for the overall period or the first subperiod. For the second subperiod, the mild segmentation APM performs best to replicate the actual returns and is consistent with all actual trading rule returns at the 5 percent significance level.

Indonesia:

Assuming the 5 percent significance level, none of the null models are completely consistent with the actual trading rule returns.

Mexico:

Assuming the 5 percent significance level, none of the null models are completely consistent with the actual trading rule returns.

Taiwan:

The mild segmentation APM perform best to replicate the actual trading rule returns and is consistent with all actual returns at the 5 percent significance level.

7.5 Discussion

The results from the standard tests indicate that the technical trading rules examined by BLL exhibit statistically significant forecast power for the Datastream Japan, Canada, Indonesia, Mexico and Taiwan indices. Since trades with a 1-day lag still lead to significant forecast power for the indices, the spurious autocorrelations due to the nonsynchronous trading are unlikely to explain the observed forecast power completely. On the other hand, despite the findings by BLL, the trading rules do not exhibit any significant forecast power for the U.S. indices (the Datastream and Dow Jones indices). Finally, the trading rules do not have significant forecast power for the Nikkei index futures.

This thesis examines the post-transaction cost profitability of the trading rules by calculating the break-even transaction costs which equate the return on the double-or-out strategy with the return on the buy-and-hold strategy. The results indicate that the break-even transaction costs for the emerging markets are high, compared with those of the developed markets. Further, the estimates of the actual transaction costs which Hill (1993) and Elkins/McSherry (1997) report indicate that the double-or-out strategy appears to be profitable relative to the buy-and-hold strategy for the Datastream Japan index, Nikkei index futures, and the three emerging markets. However, the estimates of the actual transaction costs indicate that it may not be profitable for the U.S. indices.

In contrast to the standard tests, the bootstrap tests indicate that some models among the equilibrium asset pricing models with time-varying expected returns corresponding to complete integration, mild segmentation, and complete segmentation are consistent with the actual trading rule returns for Japan, the second subperiod of Canada (1987.11-1996.12), and Taiwan, assuming the 5 percent significance level. For the Datastream Japan index, the mild segmentation APM is consistent with the actual trading rule returns for the overall period and second subperiod, while all three equilibrium models are consistent with the actual trading rule returns for the first subperiod. For the Canada (the second subperiod) and Taiwan indices, the mild segmentation APM is consistent with the actual trading rule returns. Further, the result for the Datastream Japan index is supplemented by the result from the Nikkei index futures, which indicates that all three equilibrium models are consistent with the actual trading rule returns. Thus, at least for these countries and periods, the technical rule profits seem to be explained by the risk-return relation implied by the asset pricing models. In particular, the bootstrap tests tend to fail to reject the mild segmentation APM when some of the equilibrium models are consistent with the trading rule profits which are found to be significant based on the standard test statistics. This result can be interpreted as additional evidence for the widely accepted notion that the world financial market is not fully integrated, but not completely segmented.

Some results for the Nikkei index futures appear to bring somewhat puzzling questions to this thesis, but it is possible to answer them. First, when the standard test statistics are used, the technical trading rules exhibit significant forecast power for the Datastream Japan index, but they do not exhibit significant forecast power for the Nikkei index futures. According to the cost-of-carry model, the Nikkei index futures price is expected to move together with the Datastream Japan index, which is likely to resembles closely the Nikkei stock index underlying the Nikkei index futures.[10] However, this first puzzling result may be attributable to the measurement errors due to infrequent trading and bid-ask bounce as Miller, Muthuswamy, and Whaley (1994) show. Second, the transaction cost analysis indicates that the double-or-out strategy based on the trading rules is profitable relative to the buy-and-hold strategy under the estimate for transaction costs which is provided by Hill (1993) and Elkins/McSherry (1997). However, when the time-varying expected return and risk are taken into account by using the bootstrap methodologies, the apparent profits for the Nikkei index futures are consistent with the asset pricing models which this thesis examines.

Although BLL find that the technical trading rules have significant forecast power for the Dow Jones index over the 90-year period, the results in this thesis indicate that the same trading rules can not predict the future returns on the U.S. indices when the trading rules are applied to the recent sample. Both standard and bootstrap tests unequivocally reject the hypothesis that the trading rules can generate abnormal returns for the U.S. market for the sample during 1987-1996. Of course, this result does not preclude the possibility that during the sample period of the BLL study (1887-1986), the technical trading rules actually could predict the returns on the U.S. market and acquire abnormal profits. However, unless there is a convincing reason to believe that the U.S. sample of this thesis is biased against the

[10] The returns on the stock index and index futures contract are perfectly correlated if the dividend yield of the stock index and interest rate are constant (Stoll and Whaley 1990b).

technical trading rules, it may be concluded that an opportunity for such profits has already disappeared in the U.S. market, probably because of the recent technological and institutional improvements in the processing of market-wide information as the Froot and Perold (1995) study indicates.

The results in this thesis seem to shed some light on the issue of whether the Canadian market is integrated with the U.S. market. The standard test results of the trading rules for both countries indicate that while the technical trading rules do not exhibit significant forecast power for the U.S. market, the same rules have significant, strong forecast power for the Canadian market. As discussed earlier, this contrast can be interpreted as indirect evidence for either the joint hypothesis that under market efficiency, the Canadian market is segmented from the U.S. market or the hypothesis that the Canadian market is inefficient. The bootstrap test results indicate that at least for the recent period 1987.11-1996.12, the technical rule profits observed in the Canadian market are consistent with the hypothesis that the Canadian market is efficient and is mildly segmented from the rest of the world. Thus, the inefficiency interpretation may be dismissed. Although the rest of the world includes both the U.S. and other markets, the asset pricing relation under mild segmentation highlights the importance of Canadian (local) risk premium. Thus, the results seem to be more consistent with segmentation of Canada from the U.S. than the integration for the period 1987.11-1996.12. This interpretation of the results for Canada is consistent with the study by Karolyi (1995) who provides evidence for significant investment barriers between Canada and the U.S. by examining a bivariate GARCH model similar to this thesis.

This thesis obtains the result which indicates that the trading rule returns are consistent with the mild segmentation of the Japanese equity market relative to the rest of the world. Although Harvey (1991) rejects the integration of Japan with the world market by using a single factor model, some studies indicate that Japan is integrated. The results of Campbell and Hamao (1992) are consistent with the integration of Japan with the U.S. in the context of a multi-factor model. Ferson and Harvey (1993) also present evidence that Japan is integrated with the world market by examining a multi-factor asset pricing model. Thus, the previous studies seem to suggest that Japan is integrated with other markets, but that a single factor model is not appropriate. In the context of this thesis, it may be possible to interpret the empirical model for the mild segmentation APM as a two-factor model where the domestic and foreign market returns correspond to two portfolios mimicking two different factors in the internationally integrated market. CKS present a similar interpretation.

Both the standard and bootstrap tests agree that the technical rule profits are unusual for Indonesia, Mexico, and the first subperiod of Canada. A possible interpretation for this result is that the Indonesian, Mexican, and Canadian equity markets were inefficient during the period of the sample. In particular, some institutional features of emerging markets such as highly concentrated ownership and less stringent requirements for financial disclosures might lead to a substantial degree of informational efficiency in Indonesia and Mexico. As usual, however, the joint-hypothesis problem arises. In this thesis, the trading rules are tested with the joint hypotheses of market efficiency, a certain type of international market structure and the corresponding asset pricing model. Therefore, the rejection of the joint hypotheses could be due to market inefficiency, more complicated international market structure, a wrong asset pricing model or any combinations of these component hypotheses. Thus, the question of what causes the unusual technical rule profits for Indonesia, Mexico, and the first subperiod of Canada can not be definitely answered.

When estimating parameters for the equilibrium asset pricing models, the likelihood ratio tests are conducted to test the restrictions corresponding to complete integration, mild segmentation and complete segmentation. It is of interest to compare the results from the likelihood ratio tests with those from the bootstrap tests. It seems to be demonstrated that the bootstrap tests tend to supplement the likelihood ratio tests by providing greater power. For the Datastream Japan index, the likelihood ratio tests can reject only the world CAPM for the overall period and the second subperiod; the bootstrap tests can reject the world CAPM and domestic CAPM at the 5 percent significance level, leaving only the mild segmentation

APM. Similarly, the bootstrap tests exhibit greater power than the likelihood ratio tests for Canada (for the overall period and both subperiods), Indonesia, Mexico and Taiwan. On the other hand, the two cases (the results for the first subperiod of Japan, and those for the overall period of the U.S.) lead to less power in the bootstrap tests than in the likelihood ratio tests. In both cases, forecast power of the technical rules is very week when using the standard test statistics. Except for the two cases, however, the bootstrap tests can provide additional information relative to the likelihood ratio tests due to greater power.

Chapter 8 Conclusions

One of the primary conclusions of this thesis is that taking into account time-varying expected returns is important to evaluate the profitability of technical trading rules. In this thesis, the expected returns are constrained to vary over time in a way consistent with an equilibrium asset pricing model. Therefore, if the trading rule returns are consistent with the patterns of time-variation in the expected returns implied by the model, this implies that the trading rule profits can be explained by the risk-return relation suggested by the asset pricing theory.

The technical trading rules which this thesis examines are the same as those used in BLL (1992). This thesis applies the trading rules to data on the equity indices for six countries (Japan, the U.S., and Canada as developed markets, and Indonesia, Mexico, and Taiwan as emerging markets). The results from the standard test statistics which compare the conditional mean returns on the trading rules with the unconditional mean return on the buy-and-hold strategy are as follows:

(1) The technical trading rules have considerable forecast power for future returns for the Datastream Japan, Canada, Indonesia, Mexico, and Taiwan indices. However, the trading rules do not exhibit any significant forecast power for the Nikkei index futures traded in the U.S., the Datastream U.S. index or the Dow Jones index. In particular, the results for the Dow Jones index are in contrast of those of BLL who find a large spread between buy and sell returns for the Dow Jones index, using the data up to 1986.

(2) The cross-sectional pattern of the results indicates that the technical trading rules have stronger forecast power for the emerging markets than for the developed markets. For the buy-sell spread, the average values across all trading rules and three

emerging markets is 0.2302% per day or 77.8%on an annual basis; the averages across all trading rules and developed markets with significant forecast power of the trading rules (i.e., the Japan and Canada indices) is 0.1030% per day or 29.4% on an annual basis.

(3) The results from trades with a 1-day lag after the initial emissions of signals still lead to significant forecast power for the indices for which the trading rules can predict future returns. Thus, the spurious autocorrelations due to nonsynchronous trading are unlikely to explain the technical rules' observed forecast power completely.

In addition, this thesis provides some information on the effects of transaction costs on the profitability of the trading rules by calculating the break-even transaction costs which equate the return on the double-or-out strategy with the return on the buy-and-hold strategy. The results obtained are as follows:

(4) The average break-even transaction costs across the trading rules for the emerging markets are considerably high; they range from 3.27% to 4.64% for 0-day lag trades. Among the developed markets, the average for the Datastream Japan index is the highest, 2.24%. For Canada, the average break-even cost is of moderate size, 1.6%. For the Datastream U.S. and Dow Jones indices, they are lower than those of 5 other countries (except for the Nikkei index futures), 1.06% and 0.65%, respectively. Finally, the average break-even cost for the Nikkei index futures is 0.73%.

(5) The estimates of the actual transaction costs which Hill (1993) and Elkins/McSherry (1997) report indicate that the double-or-out strategy appears to be profitable relative to the buy-and-hold strategy for the Datastream Japan index, Nikkei index futures, and the three emerging markets. However, the estimate for the U.S. index indicates that the double-or-out strategy may not be profitable for the U.S. indices.

Next, a set of asset pricing models with the time-varying expected returns are estimated for each country. Specifically, this thesis estimates the conditional asset pricing models corresponding to the complete integration, mild segmentation and complete segmentation. Using the bootstrap methodologies, the empirical distributions of the trading rule returns are constructed under each asset pricing model as a null model, and the actual trading rule returns are compared with the obtained empirical distributions. The results from the bootstrap tests are as follows:

(6) Although the standard test results indicate that the trading rules have significant forecast power for the five countries, the results from the bootstrap tests show that the trading rule profits for Japan, the second subperiod of Canada, and Taiwan are consistent with some asset pricing models at the 5 percent significance level. Further, the result for Japan is supplemented by the result for the Nikkei index futures, which indicates that all three equilibrium models are consistent with the actual trading rule returns. Thus, at least for these three countries and periods, the trading rule profits can be considered to reflect a fair compensation for the riskiness of the rules.

(7) None of the asset pricing models are consistent with the results for Indonesia, Mexico, and the first subperiod of Canada at the 5 percent significance level. Although this result may be interpreted as an indication of inefficiency in the Indonesian market, the Mexican market, and the first subperiod of the Canadian market, the joint-hypothesis problem prevents the definite answer to what would cause the result.

This thesis investigates the issue of market integration and segmentation by focusing on the relationship between the technical trading rule profits and international market structure. The overall results on this issue from the bootstrap tests indicate:

(8) Among the three asset pricing models corresponding to complete integration, mild

segmentation and complete segmentation, the asset pricing model under the mild segmentation performs best to explain the actual trading rule returns for Japan, the recent sample of Canada, and Taiwan.

Result (8) is consistent with the widely accepted notion that financial markets are not fully integrated, but are not completely segmented. The result that the actual trading rule returns are consistent with the mild segmentation of Japan is somewhat surprising. The interpretation of this result as a multi-factor model under the market integration may be possible, as suggested by the results of some previous studies (Campbell and Hamao 1992; Chan, Karolyi, and Stulz 1992; Ferson and Harvey 1993).

Finally, the results from the bootstrap simulations indicate that additional information on the market structure characterizing the equity markets examined in this thesis is provided, compared with the results from the likelihood ratio tests for the restrictions implied by the asset pricing models under various market structures:

(9) For most cases, the bootstrap tests exhibit greater power in rejecting the null models than the likelihood ratio tests.

Further research will be needed in the following directions:

The models used in this thesis assume that the relative risk aversions for the world and domestic CAPM, and the prices of risk for the asset pricing model under the mild segmentation are constant over time. This assumption may be too strong. For example, the results of Harvey (1991) and Ferson and Harvey (1993) indicate the importance of time-varying risk premias as well as time-varying risk exposures. Relating to this, Bekaert and Harvey (1995) provide evidence for the time-varying integration of the emerging markets with the world market, which can be interpreted as the time-varying relative risk aversions or prices of risk in the context of this thesis. If the relative risk aversions or the prices of risk are allowed to vary over time, some of the asset pricing models examined in this thesis may be able to explain the results for Indonesia, Mexico, and the first subperiod of Canada.

This thesis assumes that the expected returns are not affected by the exchange rate risk for the tractability. However, the importance of the exchange rate risk is empirically shown by recent studies (for example, Ferson and Harvey (1993) and Dumas and Solnik (1995)). Thus, the future research may need to use an asset pricing model which incorporates the exchange rate risk.

The bivariate setting of the domestic versus foreign markets is used to estimate the asset pricing models and simulate returns, and the foreign market is assumed to be internally integrated. However, the assumption of the integrated foreign market may not be appropriate. If the number of markets to be included in the system is increased, more complicated structure may be taken into account, with a cost of the increased number of parameters.

This thesis examines only six countries. Since the selected six countries are by no means a representative sample of the entire universe, further examinations using data on other countries may be required to ensure the robustness of the results this thesis obtains.

References

Adler , M. and B. Dumas, 1983, International portfolio choice and corporation finance: A synthesis, Journal of Finance 38, p925-984.

Alexander, G., C. Eun, and S. Jamakiramana, 1988, International listings and stock returns: Some empirical evidence, *Journal of Financial and Quantitative Analysis* 23, p35-51.

Alexander, Sidney S., 1961, Price movements in speculative markets: Trends or random walks, *Industrial Management Review* 2 (2), p7-26.

Alexander, Sidney S., 1964, Price movements in speculative markets: Trends or random walks, No. 2, in: P. Cootner, ed., *The random character of stock market prices* (MIT press, Cambridge, MA), p338-372.

Bae, Kee-Hong, 1995, Market segmentation and time variation in the price of risk: Evidence on the Korean stock market, *Pacific-Basin Finance Journal* 3, p1-29.

Bae, Kee-Hong and G. Andrew Karolyi, 1994, Good news, bad news and international spillovers of stock returns volatility between Japan and the U.S., *Pacific-Basin Finance Journal* 2, p405-438.

Bekaert, Geert and Campbell R. Harvey, 1995, Time-varying world market integration, *Journal of Finance* 50, p403-444.

Bekaert, Geert and Campbell R. Harvey, 1997, Emerging equity market volatility, *Journal of Financial Economics* 43, p29-77.

Berndt, E., B. Hall, R. Hall, and J. Hausman, 1974, Estimation and inference in nonlinear structure models, *Annals of economic and Social Measurement* 3, p653-665.

Bessembinder, Hendrik and Kalok Chan, 1995, The profitability of technical trading rules in Asian stock markets, *Pacific-Basin Finance Journal* 3, p257-284

Bessembinder, Hendrik and Kalok Chan, 1996, Market efficiency and the returns to technical analysis, Working paper, Arizona State University.

Black, Fischer, 1972, Capital market equilibrium with restricted borrowing, *Journal of Business* 1, p337-352.

Black, Fischer, 1974, International capital market equilibrium with investment barriers, *Journal of Financial Economics* 1, p337-352.

Bollerslev, Tim, 1986, Generalized autoregressive conditional heteroscedasticity, *Journal of Econometrics* 31, p307-327.

Bollerslev, T., R.Y. Chou, and K.F. Kronner, ARCH modelling in finance: A review of the theory and empirical evidence, *Journal of Econometrics* 52, p5-59.

Bollerslev, T., R.F. Engle, and J.M. Wooldridge, 1988, A capital asset pricing model with time-varying covariances, Journal of Political Economy 96, p116-131.

Bollerslev, T. and J.M. Wooldridge, 1992, Quasi-maximum likelihood estimation and inference in dynamic models with time varying covariances, *Econometric Reviews* 11, p143-172.

Breeden, D., 1979, An intertemporal asset pricing model with stochastic consumption and investment opportunities, *Journal of Financial Economics* 7, p265-296.

Brenner, M., M. Subrahmanyam, and J. Uno, 1989, The behavior of prices in the Nikkei spot and futures markets, *Journal of Financial Economics* 23, p363-383.

Brenner, M., M. Subrahmanyam, and J. Uno, 1989, Arbitrage opportunities in the Japanese stock and futures markets, *Financial Analysts Journal* March/April, p14-24.

Brock, William, Josef Lakonishok, and Blake LeBaron, 1992, Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance* 47, p1731-1764.

Buse, A., R. Korkie, and H. Turtle, 1994, Tests of a conditional asset pricing model with time-varying moments and risk prices, *Journal of financial and Quantitative Analysis* 29, p15-29.

Campbell, John, Y, 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, p373-399.

Campbell, John Y. and Yasushi Hamao, 1992, Predictable stock returns in the United States and Japan, *Journal of Finance* 47, p43-69.

Campbell, John Y., and Robert J. Shiller, 1988, The dividend price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, p195-228.

Chan, K.C. and G. Andrew Karolyi, and Rene M. Stulz, 1992, Global financial markets and the risk premium on U.S. equity, *Journal of Financial Economics* 32, p137-167.

Cho, C., C.S. Eun, and L. Senbet, 1986, International arbitrage pricing theory: An empirical investigation, *Journal of Finance* 41, p313-329.

Cole, David C., and Betty F. Slade, 1996, *Building a modern financial system: The Indonesian experience* (Cambridge University Press, New York).

Conrad, J., M. Gultekin, and G. Kaul, 1991, Asymmetric predictability of conditional variances, *Review of Financial Studies* 4, p597-622.

Conrad, Jennifer and Gautam Kaul, 1989, Mean reversion in short-horizon expected returns, *Review of Financial Studies* 2, p225-240.

Cox, J.C., J.E. Ingersoll, and S.A. Ross, 1985, An intertemporal general equilibrium model of asset prices, *Econometrica* 53, p363-384.

Craig, Alastair, Ajay Dravid, and Matthew Richardson, 1995, Market efficiency around the clock: Some supporting evidence using foreign-based derivatives, *Journal of Financial Economics* 39, p161-180.

Cumby, R. E. and D. M. Modest, 1987, Testing for market timing ability, *Journal of Financial Economics* 19, p169-189.

Dumas, Bernard and Bruno Solnik, 1995, The world price of foreign exchange risk, *Journal of Finance* 50, p445-479.

Dunn, K.B., and K.J. Singleton, 1986, Modelling the term structure of interest rates under non-separable utility and durability of goods, *Journal of Financial Economics* 17, p27-55.

Efron, B., 1979, Bootstrap methods: Another look at the jackknife, *The Annals of Statistics* 7, p1-26.

Efron, B., 1982, *The Jackknife, The Bootstrap, and Other Resampling Plans* (Society for Industrial and Applied Mathematics, Philadelphia).

Elkins/Mcsherry Co., Inc., 1997, Presentation document, Conference on Global Equity Issuance and Trading, Cancun.

Engle, Robert F., 1982, Autoregressive conditional heteroscedasticity with estimates of the variance of U.K. inflation, *Econometrica* 50, p987-1008.

Engle, Robert F. and Kenneth F. Kroner, 1995, Multivariate simultaneous generalized ARCH, *Econometric Theory* 11, p122-150.

Engle, Robert F., D. Lilien, and R.P. Robins, 1987, Estimating time-varying risk premia in the term structure: The ARCH-M model, *Econometrica* 55, p391-408.

Engle, R.F., V. Ng, and M. Rothschild, 1992, Multi-dynamic factor model for stock returns, *Journal of Econometrics* 52, p245-266.

Errunza, V. and E. Losq, 1985, International asset pricing under mild segmentation: Theory and test, *Journal of Finance* 40, p105-124.

Errunza, V. and E. Losq, 1989, Capital flow controls, international asset pricing, and investors' welfare: A multi-country framework, *Journal of Finance* 41, p1025-1037.

Errunza, V., E. Losq, and P. Padmanabhan, 1992, Tests of integration, mild segmentation and segmentation hypothesis, *Journal of Banking and Finance* 16, p949-972.

Fama, Eugene F., 1970, Efficient capital markets: a review of theory and empirical work, *Journal of Finance* 25, p383-417.

Fama, Eugene F., 1976, *Foundations of Finance* (Basil Blackwell, Oxford; Basic Books, New York).

Fama, Eugene, F., 1990, Stock returns, expected returns and real activity, *Journal of Finance* 45, p1089-1108.

Fama, Eugene, F., 1991, Efficient capital markets II, *Journal of Finance* 46, p1575-1617.

Fama, Eugene F., and M. Blume, 1966, Filter rules and stock market trading profits, *Journal of Business* 39, p226-241.

Fama, Eugene . F., and Kenneth R. French, 1988a, Permanent and temporary components of stock prices, *Journal of Political Economy* 96, p246-273.

Fama, Eugene . F., and Kenneth R. French, 1988b, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, p3-25.

Fama, Eugene . F., and Kenneth R. French, 1989, Business conditions and expected stock returns, *Journal of Financial Economics* 25, p25-50.

Ferson, Wayne E., 1990, Are the latent variables in time-varying expected returns compensation for consumption risk?, *Journal of Finance* 45, p397-430.

Ferson, Wayne E., 1995, Theory and empirical testing of asset pricing models, in: R. Jarrow, V. Maksimovic, and W.T. Ziemba (eds.), *Finance*, Handbook of Operations

Research and Management Science, Vol. 9., North-Holland, Amsterdam, p145-191.

Ferson, W.E., G.M. Constantinides, 1991, Habit persistence and durability in aggregate consumption: Empirical tests, Journal of Financial Economics 29, p199-240.

Ferson, Wayne E., Stephen R. Foerster, and Donald B. Keim, 1993, General tests of latent variable models and mean-variance spanning, *Journal of Finance* 48, p131-156.

Ferson, Wayne E., and Campbell R. Harvey, 1991, The variation of economic risk premiums, *Journal of Political Economy* 99, p385-415.

Ferson, Wayne E., and Campbell R. Harvey, 1992, Seasonality and consumption asset pricing models, *Journal of Finance* 47, p511-552.

Ferson, Wayne E., and Campbell R. Harvey, 1993, The risk and predictability of international equity returns, *Review of Financial Studies* 6, p527-566.

Ferson, Wayne E., and Campbell R. Harvey, 1996, *Fundamental Determinants of national equity market returns: A perspective on conditional asset pricing*, Working paper, 1996.

Ferson Wayne E. and Robert A. Korajczyk, 1995, Do arbitrage pricing models explain the predictability of stock returns?, *Journal of Business* 68, p309-349.

Foerster, S. and G.A. Karolyi, 1993, International listings of stocks: The case of Canada and the US, *Journal of International Business Studies* 24, p763-784.

Freedman, D., and S. Peters, 1984, Bootstrapping an econometric model: Some empirical results, *Journal of Business and Economic Statistics* 2, p150-158.

French, Kenneth R. and James M. Poterba, 1991, Were Japanese stock prices too high?, *Journal of Financial Economics* 29, p337-363.

French, R. Kenneth, G. William Schwert, and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial economics* 19, p3-29.

Froot, K.A., and A.F. Perold, 1995, New trading practices and short-run market efficiency, *Journal of Futures Markets* 15, p731-765.

Gibbons, M. R., and W. Ferson, 1985, Testing asset pricing models with changing expectations and an unobservable market portfolio, *Journal of Financial Economics* 14, p217-236.

Gultekin, N., M. Gultekin and A. Penati, 1989, Capital controls and international capital market segmentation: Evidence from Japanese and American stock markets, *Journal of Finance* 44, p849-869.

Hamao, Yasushi, and Joel Hasbrouck, 1995, Securities trading in the absence of dealers: Trades and quotes on the Tokyo Stock exchange, *Review of Financial Studies* 8, p849-878.

Hamao, Yasushi, Ronald W. Masulis, and Victor Ng, 1991, Correlations in price changes and volatility across international stock markets, *Review of Financial Studies* 3, p281-307.

Hansen, L.P., and R.J. Hodrick, 1983, Risk averse speculation in the forward foreign exchange market: An econometric analysis of linear models, in: J. Frenkel (ed.), *Exchange Rates and International Macroeconomics*, University of Chicago Press, Chicago, IL.

Hansen, L.P., and K. Singleton, 1982, Generalized instrumental variables estimation of nonlinear rational expectations models, *Econometrica* 50, p1269-1285.

Hansen, L.P., and K. Singleton, 1984, Errata, *Econometrica* 52, pp267-268.

Harvey, Campbell, 1989, Time-varying conditional covariances in tests of asset pricing models, *Journal of Financial Economics* 24, p289-318.

Harvey, Campbell, 1991, The world price of covariance risk, *Journal of Finance* 46, p111-157.

Harvey, Campbell, 1995, Predictable risk and returns in emerging markets, *Review of Financial Studies* 8, p773-816.

Hill, Joanne M., 1993, Adding value with equity derivatives: Part II, in *Derivative Strategies for Managing Portfolio Risk*, Association for Investment Management and Research: Charlottesville, VA.

Hull, John C., 1989, *Options, futures, and other derivative securities* (Prentice Hall, New Jersey).

Ito, Akitoshi, 1996, *Technical trading rules and nonlinear time series models*, Working paper, University of Western Ontario.

Jorion, Philippe and Eduardo Schwartz, 1986, Integration vs. Segmentation in the Canadian stock market, *Journal of Finance* 41, p603-616.

Karolyi, G. Andrew, 1995, A multivariate GARCH model of international transmissions of stock returns and volatility: The case of the United States and Canada, *Journal of Business and Economic Statistics* 13, p11-25.

Karolyi, G. Andrew, 1996, Stock market volatility around expiration days in Japan, Journal of Derivatives Winter p23-43.

Karolyi, G. Andrew, and Bong-Chan Kho, 1996, *Time-varying risk premium and the returns to buying winners and selling losers: Caveat emptor et venditor*, Working paper, University of Western Ontario.

Keim, Donald B. and Robert F. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, p357-390.

Kho, Bong-Chan, 1996, Time-varying risk premium, volatility, and technical trading rule profits: Evidence from foreign currency futures markets, *Journal of Financial Economics* 41, p249-290.

Levich, Richard M. and Lee R. Thomas, 1993, The significance of technical trading rule profits in the foreign exchange markets: A bootstrap approach, *Journal of International Money and Finance* 12, p451-474.

Lim, Kian-Guan, 1990, Arbitrage and price behavior of Nikkei stock index futures, *Journal of Futures Markets* 12, p151-161.

Lin, Wen-Ling, Robert F. Engle, and Takatoshi Ito, 1994, Do bulls and bears move across borders? International transmission of stock returns and volatility, *Review of Financial Studies* 7, p507-538.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, p13-37.

Lo, Andrew W., and Craig A. MacKinlay, 1988, Stock market prices do not follow random walks: Evidence from a simple specification test, *Review of Financial Studies* 1, p41-66.

Lo, Andrew W., and Craig A. MacKinlay, 1990a, An econometric analysis of infrequent trading, *Journal of Econometrics* 45, p181-11.

Lo, Andrew W., and Craig A. MacKinlay, 1990b, Data-snooping biases in tests of financial asset pricing models, *Review of Financial Studies* 3, p431-468.

Lucas, Robert E., 1978, Asset prices in an exchange economy, *Econometrica* 46, p1429-1445.

MacKinlay, A.C., and K. Ramaswamy, 1988, Index futures arbitrage and the behavior of stock index futures prices, *Review of Financial Studies* 1, p137-158.

Merrick, J., 1989, Early unwindings and rollovers of stock index futures arbitrage programs: Analysis and implications for predicting expiration day effects, *Journal of Futures Markets* 9, p101-111.

Merton, Robert, 1973, An intertemporal capital asset pricing model, *Econometrica* 41, p867-887.

Miller H.M., J. Muthuswamy, and R.E. Whaley, 1994, Mean reversion of Standard & Poor's 500 index basis changes: Arbitrage-induced or statistical illusion?, *Journal of Finance* 49, p479-513.

Mittoo, U., 1992, Additional evidence on integration in the Canadian stock markets, *Journal of Finance* 47, p2035-2054.

Nelson, Daniel B., 1991, Conditional heteroscedasticity in asset returns: A new approach, *Econometrica* 59, p347-370.

Roll. Richard, 1984, A simple implicit measure of the effective bid-ask spread, *Journal of Finance* 39, p1127-1139.

Roll, Richard, 1995, An empirical survey of Indonesian equities 1985-1992, *Pacific-Basin Finance Journal* 3, p159-192.

Ross, Stephen, 1976, The arbitrage theory of capital asset pricing, *Journal of Economic Theory* 13, p341-360.

Scholes, M. and J. Williams, 1977, Estimating betas from nonsynchronous data, *Journal of Financial Economics* 5, p309-327.

Sharpe, William, 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, p425-442.

Solnik, B., 1974, Equilibrium in international asset markets under uncertainty, *Journal of Economic Theory* 8, p500-524.

Solnik, B., 1983, International arbitrage pricing theory, *Journal of Finance* 38, p449-457.

Stehle, Richard, 1977, An empirical test of the alternative hypotheses of national and international pricing of risky assets, *Journal of Finance* 32, p493-502.

Stoll, Hans R. and Robert E. Whaley, 1983, Transaction costs and the small firm effect, *Journal of Financial Economics* 12, p57-79.

Stoll, Hans R. and Robert E. Whaley, 1986, *Expiration day effects of index options and futures*, new York University, Monograph Series in Finance and Economics.

Stoll, Hans R. and Robert E. Whaley, 1987, Program trading and expiration-day effects, *Financial Analysts Journal* March/April, p16-28.

Stoll, Hans R. and Robert E. Whaley, 1990a, Program trading and individual stock returns: Ingredients of the triple witching brew, *Journal of Business*, pS165-S192.

Stoll, Hans R. and Robert E. Whaley, 1990b, The dynamics of stock index and stock index futures returns, *Journal of Financial and Quantitative Analysis* 25, p441-468.

Stoll, Hans R. and Robert E. Whaley, 1991, Expiration-day effects: What has changed?, *Financial Analysts Journal* January/February, p58-71.

Stulz, Rene, 1981a, A model of international asset pricing, *Journal of Financial Economics* 9, p383-406.

Stulz, Rene, 1981b, On the effects of barriers to international investments, *Journal of Finance* 25, p783-794.

Stulz, Rene, 1983, Pricing capital assets in an international setting: An introduction, *Journal of International Business Studies*, Winter, p55-73.

Stulz, Rene, 1995, International portfolio choice and asset pricing: An integrative survey, in: R. Jarrow, V. Maksimovic, and W.T. Ziemba (eds.), *Finance*, Handbook of Operations Research and Management Science, Vol. 9., North-Holland, Amsterdam, p201-223.

Sweeney, Richard J., 1986, Beating the foreign exchange market, *Journal of Finance* 41, p163-182.

Sweeney, Richard J., 1988, Some new filter rule tests: Methods and results, *Journal of Financial and Quantitative Analysis* 23, p285-300.

White, H., 1980, A heteroscedasticity-consistent covariance matrix estimator and direct test for heteroscedasticity, *Econometrica* 48, p817-838.

IMAGE EVALUATION TEST TARGET (QA-3)

150mm

6"

APPLIED IMAGE, Inc
1653 East Main Street
Rochester, NY 14609 USA
Phone: 716/482-0300
Fax: 716/288-5989