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On the returns generating process and the profitability of trading rules in emerging capital markets

John Hatgioannides*, Spyros Mesomeris

Cass Business School, City University, 106 Bunhill Row, London EC1Y 8TZ, UK

Abstract

In this paper, we aim to characterize the stock return dynamics of four Latin American and four Asian emerging capital market economies and assess the profitability of popular trading rules. Using Morgan Stanley Capital International (MSCI) daily stock index prices, we find that dollar denominated returns exhibit statistically significant long-memory effects in volatility but not in the mean. ‘‘Trading’’ our findings via a number of rules, we beat the ‘‘buy-and-hold’’ benchmark strategy in all markets before transaction costs and, predominantly, in Asian markets after transaction costs. The robustness of our results casts serious doubt on the weak form efficiency of such markets.

JEL classification: C13; C15; G14; G15

Keywords: Trading rules; Emerging markets; Stock return dynamics; Long memory; Bootstrap simulations

1. Introduction

In recent years, emerging capital markets (henceforth ECM) have attracted a great deal of attention from investors and investment funds seeking to diversify their portfolios.

* Corresponding author. Tel.: +44 207 0408973; fax: +44 207 0408881.
E-mail address: j.hatgioannides@city.ac.uk (J. Hatgioannides).

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Notwithstanding their high risk, the higher sample average returns and low correlations with developed market returns are two of the distinguishing features of ECM returns (Bekaert and Harvey, 1997) that have made such markets increasingly attractive to international investors. Such characteristics, coupled with the financial liberalization process these countries have embarked on, have led to a dramatic increase in capital flows since the early 1990s, with portfolio flows (fixed income and equity) and foreign direct investment replacing commercial bank debt as the dominant sources of foreign capital (Bekaert and Harvey, 2003).

Despite the significance of ECM as important conduits of international diversification, little has been said in the literature about the statistical returns generating process, and the profitability of trading rules in these markets. The principal aim of this paper is to fill this void in the literature by modeling the dynamic behavior of stock returns in ECM and assessing the potential profitability of popular trading strategies.

Recent studies show that emerging markets tend to exhibit higher volatility (both conditional and unconditional) compared with developed markets (see, for example, De Santis and Imrohoroğlu, 1997; Bekaert and Harvey, 1997), as well as higher persistence in stock returns (see Bekaert and Harvey, 1997). Such evidence could be attributed to some form of market inefficiency offering opportunities for excess returns, even after adjusting for risk. It could also reflect a more persistent variation of risk factors in ECM.

Persistence in equity returns may be attributed to long-range dependence, or long memory, in the returns time series. Arguably, ECM are more likely to exhibit such characteristics than developed markets. Market thinness and nonsynchronous trading biases should be expected to be more severe in ECM, given their low level of liquidity (De Santis and Imrohoroğlu, 1997). Also, "learning effects" are bound to be important since investors in ECM tend to react slowly and gradually to new information (Barkoulas et al., 2000). In addition, the mounting evidence of nonnormality and non-linearities in ECM returns (Bekaert and Harvey, 1997) is consistent with a persistent (either in mean and/or volatility) return generating process in emerging markets. Recently, Cajueiro and Tabak (2004, 2005) estimate Hurst exponents and find strong long-range dependence in the volatility of ECM returns.

Such characteristics of a market suggest that technical trading rules could be profitable (see Van Der Hart et al., 2003). Technical trading analysis assumes that the patterns in past security price series will recur in the future, and can thus be used for predictive purposes. Furthermore, technical analysis may be used to uncover hidden patterns in stock returns not picked up by standard statistical tests, which can help to better forecast prices.

Two questions are being predominantly addressed in this paper: First, within the ARFIMA–FIGARCH framework, the existence of long memory in the mean and variance of ECM stock return dynamics. Second, the relative profitability over and above the buy-and-hold strategy of popular trading rules such as Moving Average and Trading Range Break strategies. The impact of transaction costs and measurement errors in returns is also examined. Furthermore, we re-evaluate the performance of the trading strategies within a risk-return framework using the Sharpe ratio statistic which characterizes whether excess – to the buy and hold – returns generated by our trading rules come at the expense of unduly higher risk.

Since the influential paper of Sullivan et al. (1999), any apparent success of trading rules has been confronted with an appropriate degree of scepticism due to data-snooping biases. In order to mitigate the possibility of reporting spurious results, in the empirical part of the paper we are employing a relatively unexplored data set; it is well known that data snooping is aggravated by repeated investigations of the same data set. As Chang et al. (2004),[1] we are using the Morgan Stanley Capital International (MSCI) daily stock index price series for eight emerging markets which fall into two geographical regions: Latin America (Argentina, Brazil, Chile, Mexico) and Asia (Indonesia, Philippines, Taiwan, Thailand). A mix of different exchanges is included in our sample and the stock markets examined vary in age, size, and spread of securities traded. Moreover, we are interested in comparing results across regions, given that Latin American markets have been more "open" during the late 1980s and 1990s compared to their Asian counterparts.

Our methodology follows the studies by Brock et al. (1992) and Sullivan et al. (1999), as standard statistical tests are augmented by the bootstrap procedure to carry out statistical inferences on trading rule profitability and ability to forecast future price changes. Chang et al. (2003, 2004) use a similar approach to investigate whether emerging stock markets that we also examine in our study are weak form efficient. However, our study significantly differs in that we decide on the particular specification of the double long-memory ARFIMA–FIGARCH model that is empirically supported in each market. We conduct bootstrap simulations of the underlying returns process using the estimated parameters and standardized residuals for the fitted model and apply our trading rules on each of the simulated series. The ability of the econometric model to generate trading rule results consistent with actual data is examined.

The remainder of this paper is organized as follows. In Section 2 we present the econometric framework employed and its rationale. Section 3 addresses the trading strategy methodology and the bootstrap procedure. Section 4 presents the data set. Section 5 analyses our empirical results and assesses their significance. Finally, Section 6 concludes the paper.

2. The econometric framework

2.1. The ARFIMA–FIGARCH model

In the context of ECM, recent studies by Barkoulas et al. (2000) and Wright (1999) report evidence of long memory in the mean using the Geweke and Porter-Hudak (1983) estimator. Furthermore, Cajueiro and Tabak (2004, 2005) report that the conditional volatility of asset returns displays long-memory or long-range dependence. As a result, a non-linear model embodying the long-memory feature both in the mean and variance of returns could potentially capture adequately the statistical features of ECM return dynamics.

The double long-memory ARFIMA–FIGARCH model is the starting point in our description of the dynamic return generating process in ECM.[2] Throughout the paper we use $\{x_t\}$ to denote the price series and $\{y_t\}$ the continuously compounded returns, where $y_t = \log(x_t) - \log(x_{t-1})$.

In the spirit of Baillie et al. (2002), we parametrize the conditional mean as an ARFIMA (5,d,0) process and the conditional variance as a FIGARCH(1,δ,1) process:

[1] Chang et al. (2003) initially used ECM national stock indices. Subsequently, Chang et al. (2004) re-worked their former results on ECM weak form efficiency using MSCI data, though not for the same period that we examine. The two studies, independently of one another, are, to the best of our knowledge, the only ones carried out on the MSCI dataset.

[2] For a survey, see Baillie (1996).

$$\rho(L)(1-L)^d(y_t-\mu)=u_t$$

$$u_t=z_t\sigma_t,\quad z_t\sim\text{i.i.d. } N(0,1)$$

$$\sigma_t^2=\omega+\beta\sigma_{t-1}^2+\left[1-\beta L-(1-\phi L)(1-L)^\delta\right]u_t^2 \tag{1}$$

where d and δ are the long-memory parameters, L is the lag operator, $\rho(L)=1-\sum_{j=1}^{5}\rho_jL^j$, μ is the unconditional mean of the process y_t, u_t is the white noise, and all the roots of $\rho(L)$ lie outside the unit circle. The lag order structure for the autoregressive component of the mean equation is chosen so as not to over-parametrize the model, while adequately describing the short-run dynamics.

It is clear that under homoskedasticity the process in Eq. (1) reduces to an ARFIMA(5,d,0) model. The conditional volatility dynamics follow a FIGARCH(1,δ,1) specification which imposes an ARFIMA structure on u_t^2 and implies an undefined unconditional variance for all δ. The parameter δ captures the long-memory effect, while ϕ and β describe the short-run effects. The FIGARCH(1,δ,1) model nests both the stable (for $\delta=0$) and integrated (for $\delta=1$) GARCH(1,1) specifications. When $0\le\delta\le 1$, the FIGARCH model is strictly stationary.[3]

Model (1) can be estimated, under the assumption of normally distributed innovations, by using non-linear optimization procedures to maximize the Likelihood function below:

$$\text{Loglik}(\theta,u_t)=(-T/2)\ln(2\pi)-(1/2)\sum_{t=1}^{T}\left[\ln\left(\sigma_t^2\right)+u_t^2\sigma_t^{-2}\right] \tag{2}$$

where $\theta\equiv(\mu,\rho_j,d,\omega,\delta,\beta,\phi)$.

Since most returns series are not well described by the conditional normal density, the Quasi Maximum Likelihood Estimation (QMLE) technique of Bollerslev and Wooldridge (1992) is invoked to allow for asymptotically valid inference. Starting with the ARFIMA(5,d,0)–FIGARCH(1,δ,1) process in Eq. (1), we arrive at the most parsimonious representation for the returns process in each market using the general-to-specific methodology and a number of diagnostic tests to choose between competing nested models. We use the Ljung–Box (Q) statistic on standardized and squared standardized residuals to test the null hypothesis of no autocorrelation up to order 50. We also conduct the BDS test of Brock et al. (1996) on standardized residuals to see if higher order non-linearities are present in the stock index returns that are not captured by the model. Finally, we employ the Akaike (AIC) and Schwarz (SBC) criteria to compare the different model specifications and decide on lag order selection issues.

2.2. Dealing with structural breaks

Since the markets in our sample have gone through a gradual process of market integration and suffered a number of financial crises (the Asian crisis in September 1997, the Mexican peso crisis in January 1994, the Brazilian crisis in January 1999, and the Argentinean crisis in late 2001), one could argue that regime-switching and time-varying parameter models are suitable

[3] For a full treatment of the ARFIMA model see, for example, Granger and Joyeux (1980) and Baillie et al. (1996) for the FIGARCH process.

candidates for the returns data generating process in ECM. We chose not to estimate these models for the following reasons.

First, Bekaert et al. (2002) argue that regime-switching and time-varying parameter models are difficult to specify and often statistically rejected. There is no model that specifies the economic mechanism (or the dynamics involved) that moves a country from segmented to integrated status. In addition, the liberalization process itself is quite complex and difficult to date, and it is unlikely that dates of capital market reforms will correspond to the true date of market integration. For example, there are ways to circumvent capital controls through American Depository Receipts or country funds, even though the market may be technically closed to foreign investors. In particular, the countries covered in this study were accessible to international investors around the beginning of our sample period (see Section 4).

Second, regime shifts or structural breaks (be they from market liberalization measures or some financial crisis) do not feature prominently in the returns series of ECM, in contrast with other financial and macroeconomic series. Bekaert et al. (2002) find it difficult to detect breaks in the US dollar returns series of emerging markets using endogenous break procedures and attribute the lack of structural breaks to the noisiness of the returns series.

Third, it has been suggested that non-linear-in-the-mean models such as regime-switching or threshold autoregression models underperform simple "random-walk-type" models in explaining observed features of the data. In the context of emerging markets, Edwards et al. (2003) investigate AR(1), AR(1)−GARCH(1,1), and AR(1)−EGARCH(1,1) specifications for Argentina, Brazil, Chile, Mexico, South Korea, and Thailand. They find that during the 1990−2001 post-liberalization period, the bull phases of the emerging markets they examine are consistent with "random walk beyond a simple autocorrelation" type statistical models of returns; bear phases, though, exhibit some departures in the sense of large negative returns at the end of the phase. Nevertheless, regime-switching models or processes with stochastic volatility perform worse than the simple models they use in fitting the features of the data.

3. Technical trading rules and the bootstrap

3.1. Previous evidence

Bessembinder and Chan (1995) find that the Brock et al. (1992) trading rules applied to the daily equity market indices of six Asian countries between 1975 and 1989 can be profitable, particularly in Malaysia, Thailand, and Taiwan, even when trading costs are considered. Ratner and Leal (1999) report strong evidence of forecasting ability for moving-average rules in 10 emerging equity markets in Latin America and Asia using daily, inflation-adjusted, index level returns from January 1982 through April 1995. In fact, 82 rules out of the 100 rules tested provide the correct indication of the index return change if statistical significance is disregarded. In particular, Taiwan, Thailand and Mexico emerge as markets where technical trading strategies can consistently beat the buy-and-hold after transaction costs. Strong support for the predictability of trading rules is also provided by Gunasekarage and Power (2001) in the context of four South Asian stock markets and by Parisi and Vasquez (2000) for Chile. Chang et al. (2003, 2004), using multivariate variance ratio statistics and moving average and Trading Range Break rules, show that emerging equity market indices in Latin America and Asia are predictable; however, only few trading rules generate positive excess returns after transaction costs and a buy-and-hold strategy are taken into account.

3.2. Trading strategy methodology

To avoid compounding data-snooping concerns, we do not attempt to exploit patterns in the data on an *ex post* basis. Instead, we apply eight Variable Length Moving Average (henceforth VMA) models and six Trading Range Breakout (henceforth TRB) rules (resistance and support levels) used by Brock et al. (1992) to index portfolios of the eight ECM, and report results for all rules.[4] These rules appear often in previous academic research, and though subject to a survivorship bias, they were very popular with traders as of the late 1980s, often forming the basis for more complicated trading schemes.[5]

We adopt the *t*-statistics used by Brock et al. (1992) to test the null hypothesis that mean returns generated by technical trading rules equal the returns derived by the buy-and-hold strategy. However, since the return distribution in each ECM (see Tables 1 and 2) is not normal, the trading strategies may simply capture the dependencies in the data. To address this issue and assess the statistical significance of our trading rules, a simple i.i.d. bootstrap procedure is performed to calculate critical values[6]: 500 new time series of returns are generated for each market by randomly drawing from the original series with replacement, as in Ratner and Leal (1999). The bootstrapped returns are then exponentiated back to form a bootstrapped price index series with initial value equal to 1 and the technical trading rules that were applied to the original series are also applied to this index. The fraction of (simulated buy−sell) statistics which are at least as large as the (buy−sell) statistics from the actual series is used to compute simulated *p*-values.

As we are also interested in the profitability of the technical trading rules to a trader who implemented the signals during the sample period in each market, we calculate annualized excess returns for each trading rule net of transaction costs and the buy-and-hold strategy.[7] Following Bekaert et al. (1998) and Van Der Hart et al. (2003) we use a flat 1% one-way trading cost across all ECM that we focus on in our paper.

In addition to evaluating the strategies quantitatively on a return basis, we utilize the Sharpe ratio statistic as in Sullivan et al. (1999) to provide a risk adjusted performance measure of the trading rules. We follow standard practice and measure excess returns − net of the buy-and-hold strategy and transaction costs − relative to the benchmark of a risk-free interest rate, which implies that trading rules earn the risk-free rate on days where a neutral signal is generated.[8]

Finally, we investigate the sensitivity of returns to implementation of a one-day lag, in which, technical trading returns are measured with reference to the closing index value one

[4] For a detailed description of the formulation of our trading rules, see Hatgioannides and Mesomeris (2003).

[5] Despite the popularity among traders of the simple trading rules that we consider, we acknowledge the possibility that data-snooping biases might still be present in our empirical analysis. Although beyond the scope of this paper, it is always possible that the complete Sullivan et al. (1999) methodology, when applied to the ECM data that we use, might reveal that the trading rule results we report in the empirical part of the paper (see Section 5) are not statistically significant when compared to a cross-section of the "best rules" in bootstrap simulations of the whole universe of trading rules considered by Sullivan et al. (1999). We thank an anonymous referee for pointing out such a possibility.

[6] We thank an anonymous referee for suggesting this analysis.

[7] Note that transaction costs are imputed to the first buy and sell signals.

[8] Sullivan et al. (1999) note that since the volatility of daily interest rates is substantially smaller than that of daily stock returns, the main effect of including the interest rate in the Sharpe ratio is that of a (time-varying) drift adjustment.

Table 1
Summary statistics for daily and 10-day returns in Asian markets

	Philippines (PHI)	Taiwan (TAI)	Thailand (THA)	Indonesia (IND)
Panel A: Daily returns				
Mean	0.000056 (1.5%)	0.000194 (5.1%)	−0.000043 (−1.1%)	0.000048 (1.3%)
Standard deviation	0.0176	0.0214	0.0220	0.0290
Skewness	0.7188	0.0115	0.7033	0.2030
Kurtosis	12.8794	2.4060	9.1972	43.7281
Minimum	−0.1094	−0.113	−0.1444	−0.4308
Maximum	0.2197	0.1266	0.1810	0.4451
Jarque−Bera	4257[0.00]	520[0.00]	2563[0.00]	19229[0.00]
ADF value	27.27[0.00]	−26.37[0.00]	−27.69[0.00]	−26.82[0.00]
Autocorrelation statistics for daily returns				
$\rho(1)$	0.1831^b	0.0631^b	0.1886^b	0.1907^b
$\rho(2)$	0.0098	0.0454^b	0.0297	0.0661^b
$\rho(3)$	−0.0029	0.0430^b	−0.0163	−0.0231
$\rho(4)$	0.0056	−0.0183	0.0119	-0.0782^b
$\rho(5)$	−0.0281	0.0045	-0.0446^b	0.0130
$\rho(10)$	0.0282	0.0196	0.0428^b	0.0624^b
$\rho(100)$	−0.0224	0.0177	−0.0009	0.0213
Autocorrelation statistics for daily squared returns				
$\rho(1)$	0.1657^b	0.1677^b	0.2143^b	0.2719^b
$\rho(2)$	0.0897^b	0.2902^b	0.1927^b	0.1278^b
$\rho(3)$	0.0900^b	0.1833^b	0.2627^b	0.1653^b
$\rho(4)$	0.0467^b	0.1983^b	0.0932^b	0.1890^b
$\rho(5)$	0.0689^b	0.1692^b	0.1312^b	0.1960^b
$\rho(10)$	0.0707^b	0.2783^b	0.1732^b	0.1072^b
$\rho(100)$	0.0234	0.0912^b	0.0509^b	0.0360^b
Bartlett standard error: 0.0320				
Panel B: Ten-day returns				
Mean	0.00056	0.0019	−0.00043	0.00048
Standard deviation	0.0621	0.0746	0.0822	0.0960
Skewness	−0.2428	−0.4259	−0.0477	0.8371
Kurtosis	1.9275	1.3549	3.1908	6.8698

Notes: The daily MSCI index series is from January 1, 1988 through May 30, 2002. Returns are measured as log differences of the index level over the full sample. Numbers in parenthesis next to daily means are annualized returns assuming 260 trading days per year. Ten-day returns are based on 10-day non-overlapping periods. $\rho(i)$ is the estimated autocorrelation coefficient at lag i for each series. Coefficients marked with ^{b} indicate significant autocorrelations at the 5% level. The Bartlett standard error is calculated as $1.96/\sqrt{T}$, where T is the sample length, and is an approximate guide to the significance of autocorrelations statistics.

day after a trading signal is initiated. Omitting the first day returns eliminates the bias in measured returns attributable to nonsynchronous trading if each security trades during the intervening day. This is not an unreasonable assumption as our indices are composed of large and liquid securities.

3.3. The model-based bootstrap methodology

The purpose of employing model-based bootstrap methodologies in conjunction with technical trading rules is twofold. First, it is possible to investigate whether the specified statistical processes for the generation of stock returns in ECM can reproduce technical trading rule

Table 2
Summary statistics for daily and 10-day returns in Latin American markets

	Mexico (MEX)	Brazil (BRA)	Argentina (ARG)	Chile (CHI)
Panel A: Daily returns				
Mean	0.000766 (20.0%)	0.000463 (12.0%)	0.000305 (8.0%)	0.000439 (11.4%)
Standard deviation	0.0198	0.0289	0.0410	0.0128
Skewness	−0.0759	−0.4592	−2.8740	−0.5036
Kurtosis	12.6393	7.9084	90.1098	11.6083
Minimum	−0.2176	−0.2635	−0.9270	−0.1623
Maximum	0.1784	0.2123	0.4559	0.0870
Jarque−Bera	5038[0.00]	2514[0.00]	24327[0.00]	4124[0.00]
ADF value	−26.30[0.00]	−25.36[0.00]	−29.54[0.00]	−25.12[0.00]
Autocorrelation statistics for daily returns				
$\rho(1)$	0.1288^b	0.1473^b	−0.0309	0.2287^b
$\rho(2)$	−0.0160	0.0563^b	-0.1461^b	0.0390^b
$\rho(3)$	0.0086	0.0316	0.0697^b	−0.0135
$\rho(4)$	0.0153	0.0159	−0.0094	0.0121
$\rho(5)$	0.0107	0.0147	-0.0493^b	0.0355^b
$\rho(10)$	0.0455^b	0.0097	0.0210	0.0435^b
$\rho(100)$	0.0157	0.0293	0.0113	0.0094
Autocorrelation statistics for daily squared returns				
$\rho(1)$	0.2591^b	0.2722^b	0.0773^b	0.1045^b
$\rho(2)$	0.1375^b	0.2310^b	0.1907^b	0.0748^b
$\rho(3)$	0.1365^b	0.1965^b	0.0235^b	0.1022^b
$\rho(4)$	0.0922^b	0.0949^b	0.0556^b	0.0391^b
$\rho(5)$	0.1142^b	0.0846^b	0.0897^b	0.0459^b
$\rho(10)$	0.0991^b	0.1678^b	0.0991^b	0.0385^b
$\rho(100)$	−0.0044	0.0234	0.0065	−0.0059
Bartlett standard error: 0.0320				
Panel B: Ten-day returns				
Mean	0.00766	0.00463	0.00305	0.00439
Standard deviation	0.0686	0.1083	0.1130	0.0510
Skewness	−0.4269	−1.4365	0.985	−0.1428
Kurtosis	3.3692	9.7238	5.8639	1.1649

Notes: The daily MSCI index series is from January 1, 1988 through May 30, 2002. Returns are measured as log differences of the index level over the full sample. Numbers in parenthesis next to daily means are annualized returns assuming 260 trading days per year. Ten-day returns are based on 10-day non-overlapping periods. $\rho(i)$ is the estimated autocorrelation coefficient at lag i for each series. Coefficients marked with ^{b} indicate significant autocorrelations at the 5% level. The Bartlett standard error is calculated as $1.96/\sqrt{T}$, where T is the sample length, and is an approximate guide to the significance of autocorrelations statistics.

results consistent with the actual data. In other words, the actual trading rule results act as a specification test for the underlying process (Brock et al., 1992). Second, we can examine the standard deviations of returns during buy and sell periods relative to the buy-and-hold benchmark.

The application of the bootstrap methodology in combination with technical analysis is not particularly new to the finance literature.[9] In the spirit of Brock et al. (1992), we investigate

[9] See Brock et al. (1992), Bessembinder and Chan (1998), and Ratner and Leal (1999).

whether the estimated ARFIMA–FIGARCH models for the eight ECM are in agreement with, or rejected by, the trading rule results. Our methodology differs from previous studies in developed markets in that we incorporate the stochastic properties of both the mean and volatility of the original returns series.

We use the model-based bootstrap methodology inspired by Freedman (1981), as well as the application in Andersson and Gredenhoff (1998) who bootstrap autoregressive and heteroskedastic models. Our bootstrap procedure consists of 500 replications for the selected model for each market.[10] We then generate distributions for the buy, sell, buy–sell returns, and standard deviations of buy and sell statistics under the simulated null models for each market, by applying each and every VMA and TRB strategy tested on actual data on the simulated series as well. The null hypothesis that trading rule results from the observed data are consistent with statistics from the simulated data is rejected at the α percent level if statistics from the actual indices used are greater than the α percent cutoff of the simulated returns under the adopted models.

4. Data

The data set consists of Morgan Stanley Capital International (MSCI) daily stock index prices which do not include dividends from January 1, 1988 to May 31, 2002 – a total of 3761 daily observations – for eight emerging markets which can be grouped into two geographical regions: Latin America (Argentina, Brazil, Chile, Mexico) and Asia (Indonesia, Philippines, Taiwan, Thailand).[11] The MSCI indices are constructed to provide benchmarks that accurately represent the opportunities available to the institutional investor. It is estimated that over 90% of international institutional equity asset holdings in the US are benchmarked to MSCI indices.[12] The market indices are consistently computed across different markets and are therefore directly comparable. The component securities are free float adjusted and screened by size and liquidity. Indices are constructed so as not to double-count those stocks multiple listed on foreign exchanges. In particular, the MSCI "Free" indices we use are designed to fully reflect investable opportunities for international institutional investors, by taking into account local market restrictions on share ownership by foreigners. The S&P/IFC Investible Indices are directly comparable, but date back only to October 1995 on a daily basis.

As reported in Bekaert and Harvey (2000), official liberalization dates for the countries concerned are clustered in the late 1980s–early 1990s period. Nevertheless, markets were accessible to foreign investment prior to 1988 through country funds, except for Argentina (the first country fund was introduced in October 1991),[13] Chile (September 1989), and Indonesia (January 1989). Another indicator of the "degree of liberalization" is a measure of the intensity of capital controls as in Edison and Warnock (2003). At around the start of our sample period, foreign ownership restrictions in Asian countries were quite high, declined over the course of the 1990s, and were greatly relaxed during the 1997/1998 Asian financial crisis. The Latin American countries, however, opened up to foreign investment far earlier and far more extensively than their Asian

[10] Details available upon request.

[11] The markets examined in this study have a relatively high proportion (measured by value) of daily trade by foreigners. For example, in Thailand and Indonesia the proportion of daily trade by foreigners averaged 43% and 52%, respectively, in 1997, while in Korea and Malaysia it was only around 7% (source: S&P Emerging Market Fact Book and IMF), reflecting the aggressive local trading nature of the latter markets.

[12] www.msci.com.

[13] Note, however, that the official liberalization date for Argentina is November 1989.

counterparts. Edison and Warnock's measure suggests that Argentina's equity market was almost completely open to foreign investment before our sample started, Mexico opened its market by 1990 and Brazil followed shortly thereafter. Chile relaxed its controls in the early 1990s, but instituted controls in the mid-1990s against short-term flows.

Throughout this study we focus on dollar denominated series that are most relevant for international investors, and because local currency returns are very erratic due to occasional bursts of hyperinflation in some emerging markets, especially Argentina and Brazil.

Finally, for the calculation of the Sharpe ratio statistics, we use the daily US Treasury bill yield series between January 1, 1988 and May 31, 2002 obtained from Kenneth French's website.

5. Empirical results

5.1. Summary statistics

Tables 1 and 2 report summary statistics for one-day and 10-day (non-overlapping) US dollar returns of the Asian and Latin American markets, respectively. The buy-and-hold strategy (unconditional) returns over the whole sample period are higher in the Latin American countries (ranging from 8.0% annualized in Argentina to 20% in Mexico) than the Asian markets (from −1.1% in Thailand to 5.1% in Taiwan), and do not seem to come at the expense of higher risk (excluding Argentina). The Asian market daily returns exhibit positive skewness, while Latin American market returns are negatively skewed. This difference in skewness may partly be attributed to the Latin American economies being more integrated than the Asian markets over our sample (see Bekaert et al., 1998). Stock index returns from all markets are found to be leptokurtic and the Jarque–Bera normality test indicates that all the eight return series are not normal (p-values in brackets). Augmented Dickey–Fuller (ADF) tests indicate that stock returns are generated by stationary stochastic processes.

Autocorrelation statistics for daily returns are only significant for short lags in all cases. However, squared returns have many lags of significantly positive sample autocorrelations, particularly the Asian markets, which are bigger in absolute value than the corresponding returns autocorrelations. This suggests that short-memory models are probably adequate for capturing dynamics in the conditional mean, while conditional volatility exhibits a more persistent autocorrelation structure.[14]

5.2. Econometric results

In Table 3 we present the results of estimated parsimonious specifications of the ARFIMA–FIGARCH model (1) for each country. In all markets, we fail to reject the null of no fractional integration in the conditional mean.[15] This is in contrast with the studies by Wright (1999) and Barkoulas et al. (2000) which report some evidence in favor of long memory in emerging

[14] Plots of autocorrelation functions of daily returns in all markets do not reveal persistence, in contrast with plots of squared and absolute autocorrelations. The figures are not shown here to conserve space and are available upon request.

[15] We recognize that the span of the data is important for long-memory inference. For this reason, and before making a final decision for the significance of d, we experimented with both autoregressive and moving-average parameters in the conditional mean equation, and with no long memory in the conditional variance to avoid the possibility of over-parametrizing our model. We found that including δ does not affect the inference on d.

Table 3
Econometric models for Asian and Latin American market daily returns

	PHI	TAI	THA	IND	MEX	BRA	ARG	CHI
μ	0.0538[c] (0.030)	0.0704[c] (0.039)	0.0373 (0.030)	0.0348 (0.030)	0.1532[a] (0.020)	0.1039[a] (0.039)	0.0778[b] (0.036)	0.0128 (0.013)
ρ_1	0.1805[a] (0.018)	0.0477[a] (0.018)	0.1551[a] (0.019)	0.2004[a] (0.021)	0.1789[a] (0.018)	0.1454[a] (0.018)	0.0939[a] (0.017)	0.2759[a] (0.018)
ρ_2		0.0414[a] (0.018)	0.0541[b] (0.018)	0.0433[b] (0.023)			−0.0474[a] (0.018)	−0.0547[a] (0.018)
ρ_3		0.0339[b] (0.015)					0.0395[b] (0.019)	
ω	0.1468[a] (0.026)	0.3474[a] (0.059)	0.2085[a] (0.038)	0.1491[a] (0.025)	0.3286[a] (0.048)	0.1522[a] (0.045)	0.1422[a] (0.026)	0.1355[a] (0.019)
β	0.5518[a] (0.061)	0.2721[a] (0.037)	0.2027[a] (0.036)	0.1785[a] (0.036)	0.1313[a] (0.046)	0.6008[a] (0.061)	0.7461[a] (0.035)	0.2495[a] (0.046)
ϕ	0.1390[a] (0.047)					0.1514[a] (0.037)	0.1138[a] (0.035)	
δ	0.5244[a] (0.073)	0.3231[a] (0.059)	0.3614[a] (0.031)	0.4912[a] (0.029)	0.3563[a] (0.040)	0.5538[a] (0.064)	0.7677[a] (0.050)	0.4340[a] (0.044)
$\ln(L)$	−6954	−7791	−7459	−7209	−7250	−8753	−8988	−5801
Skewness	1.27	−0.03	0.13	0.57	−0.42	−0.58	−0.26	−0.39
Kurtosis	25.87	4.67	6.76	12.17	6.53	7.04	6.72	10.61
$Q(50)$	52.36	62.54	63.35	64.01	58.53	61.76	56.73	63.36
$Q^2(50)$	5.16	64.21	53.04	19.32	37.37	39.68	41.10	61.50
BDS	1.55	−0.61	1.68[c]	1.88[c]	−0.71	0.97	0.21	−0.17

Notes: Results are for returns ×100. Only parsimonious specifications of model (1) are presented for each market. QMLE asymptotic standard errors are in parentheses next to corresponding parameter estimates. [a], [b], and [c] denote significance at the 1, 5, and 10% levels, respectively. The quantity $\ln(L)$ is the value of the maximized log likelihood. Skewness and Kurtosis refer to the standardized residuals. The $Q(50)$ and $Q^2(50)$ statistics are the Ljung–Box test statistics for 50 degrees of freedom to test for serial correlation in the standardized and squared standardized residuals, respectively. In all cases the Ljung–Box statistics are insignificant at the 5% level. We also report the BDS test statistic of Brock et al. (1996) for standardized residuals.

market stock returns.[16] Instead, we find that conditional mean dynamics seem to be characterized by non-trivial low-order autoregressive components. These results add to the mounting evidence of positive persistence of ECM returns and are in line with Bekaert (1995) who suggests that, in emerging markets, it is often possible to predict future returns using only lagged returns.

As far as conditional volatility dynamics are concerned, the fractional differencing parameter in the volatility (δ) is significantly different from zero in all markets, implying fractional integration. Note that δ is always in the stationary region (between 0 and 1). The Q statistics and the model selection criteria (AIC/SBC) favor the FIGARCH to either the GARCH(1,1) or IGARCH(1,1) error specifications. In addition, a robust Wald test for the null hypothesis of a stationary GARCH(1,1) model versus a FIGARCH(1,δ,1) gave numerical values ranging from 51.89 in Philippines to 429.93 in Indonesia, providing overwhelming rejections of the GARCH(1,1) formulation in all markets. Our results are in line with Cajueiro and Tabak (2005) who employ a "rolling sample" approach to estimate Hurst exponents for squared and absolute emerging market returns (including the markets in this study), and find that ECM possess strong long-range dependence in volatility.

The Q statistics of the preferred model specifications in Table 3 fail to reject the null hypothesis of no autocorrelation in the standardized and squared standardized residuals. Also, the BDS test statistic on the standardized residuals does not produce significant evidence against the null hypothesis of identically and independently distributed residuals. The preferred models for the Asian markets are as follows: AR(1)−FIGARCH(1,δ,1) for Philippines, AR(3)−FIGARCH (1,δ,0) for Taiwan, AR(2)−FIGARCH(1,δ,0) for Indonesia, AR(2)−FIGARCH(1,δ,0) for Thailand. For the Latin American markets: AR(1)−FIGARCH(1,δ,0) for Mexico, AR(2)−FIGARCH(1,δ,0) for Chile, AR(1)−FIGARCH(1,δ,1) for Brazil, and AR(3)−FIGARCH(1,δ,1) for Argentina.

5.3. Trading rule results

Trading rule returns (%) are presented for Asian and Latin American markets in Tables 4 and 5, respectively. The rows labeled "Buy" and "Sell" represent the average daily returns conditional on buy and sell signals. The difference between "Buy" and "Sell", denoted as "Buy−Sell", can be realized by executing the signals. The significance of trading rule returns is evaluated using simulated p-values from the i.i.d. bootstrap (see Section 3.2).[17] Note that the significance of mean buy−sell returns of TRB rules is gauged against the unconditional 10-day return. Throughout, we only present results with the nonsynchronous trading correction which are slightly more conservative than returns without the one-day lag correction.[18] Our results show that the predictability in emerging markets cannot be attributed to nonsynchronous measurement biases.

[16] Both Wright (1999) and Barkoulas et al. (2000) use the Geweke and Porter-Hudak (1983) estimator which is not robust to short-run dynamics. See Baillie (1996) for interesting comments on semi-parametric estimation procedures.

[17] Tables 4 and 5 report only the p-values for the buy−sell differences based on the buy−sell statistic of Brock et al. (1992).

[18] There are some significant discrepancies between TRB rule results with and without the one-day lag correction in some markets. This is because there is a small number of buy and sell days compared to VMA rules. The one-day lag before a trade takes place and the fixed-length 10-day holding period after each signal imply that 20% of the rule returns are different when one compares nonsynchronous adjusted to non-adjusted results. Analytical results are available upon request.

Table 4
Results for technical trading rules in Asian markets (%)

	PHI		TAI		THA		IND	
	VMA	TRB	VMA	TRB	VMA	TRB	VMA	TRB
(1,50,0)								
Buy	0.19	2.08	0.19	1.83	0.21	1.37	0.29	3.29
Sell	−0.20	−1.47	−0.18	−1.38	−0.24	−1.07	−0.24	−1.92
Buy−sell	0.39	3.55	0.37	3.21	0.45	2.44	0.53	5.20
p-value	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.01[a]	0.00[a]	0.00[a]
(1,50,0.01)								
Buy	0.23	2.43	0.23	2.41	0.23	1.09	0.27	4.33
Sell	−0.21	−1.64	−0.19	−1.03	−0.26	−0.45	−0.32	−2.18
Buy−sell	0.44	4.07	0.42	3.43	0.49	1.54	0.59	6.50
p-value	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.10[c]	0.00[a]	0.00[a]
(1,150,0)								
Buy	0.10	1.47	0.11	1.20	0.08	1.13	0.09	4.69
Sell	−0.14	−1.49	−0.12	−3.22	−0.11	0.08	−0.20	−2.08
Buy−sell	0.23	2.96	0.22	4.42	0.19	1.06	0.29	6.77
p-value	0.00[a]	0.00[a]	0.02[b]	0.00[a]	0.10	0.22	0.03[a]	0.00[a]
(1,150,0.01)								
Buy	0.09	1.46	0.11	2.23	0.08	1.11	0.10	7.23
Sell	−0.14	−0.53	−0.12	−2.49	−0.12	2.10	−0.21	−2.53
Buy−sell	0.23	1.99	0.23	4.72	0.20	−0.99	0.31	9.76
p-value	0.00[a]	0.08[c]	0.02[b]	0.00[a]	0.11	0.70	0.02[b]	0.00[a]
(5,150,0)								
Buy	0.08		0.09		0.04		0.08	
Sell	−0.11		−0.092		−0.08		−0.17	
Buy−sell	0.20		0.19		0.12		0.25	
p-value	0.00[a]		0.01[b]		0.13		0.01[a]	
(5,150,0.01)								
Buy	0.08		0.10		0.04		0.09	
Sell	−0.11		−0.09		−0.09		−0.15	
Buy−sell	0.19		0.19		0.14		0.23	
p-value	0.00[a]		0.01[b]		0.10[c]		0.02[b]	
(1,200,0)								
Buy	0.06	1.66	0.09	0.20	0.06	1.58	0.12	4.94
Sell	−0.12	−1.82	−0.11	−3.83	−0.11	−0.24	−0.19	−1.94
Buy−sell	0.18	3.47	0.20	4.03	0.17	1.82	0.32	6.88
p-value	0.01[b]	0.00[a]	0.03[b]	0.01[a]	0.09[c]	0.11	0.00[a]	0.00[a]
(1,200,0.01)								
Buy	0.07	2.74	0.09	0.73	0.07	1.76	0.12	6.92
Sell	−0.13	−0.65	−0.11	−2.55	−0.12	1.94	−0.20	−2.02
Buy−sell	0.20	3.39	0.20	3.29	0.18	−0.18	0.32	8.94
p-value	0.00[a]	0.01[b]	0.03[b]	0.02[b]	0.10	0.50	0.00[a]	0.00[a]
Average	0.26	3.24	0.25	3.85	0.24	0.95	0.35	7.34
Buy-and-hold	0.01	0.10	0.19	1.94	−0.00	−0.04	0.00	0.05

Notes: VMA refers to Variable Length Moving Average rules, and TRB to Trading Range Break rules. Rules are defined as (S, L, B), where S is the length of the short moving average (represents nothing in the case of TRB rules), L is the length of the long moving average (represents the number of days over which maximum and minimum prices are calculated in the case of TRB rules), and B is the percentage band. Buy, sell, and buy−sell returns are daily averages (%) from following the buy and sell signals with a one-day lag over the whole sample period. The row labeled *p*-value is based on the buy−sell statistic of Brock et al. (1992), and reports the fraction of simulated statistics which are at least as large as the buy−sell statistic from the original series. The [a], [b], and [c] denote significance at the 1, 5, and 10% levels, respectively. The row labeled Average reports the simple average of the buy−sell spread across all rules. The row labeled Buy-and-hold reports average daily (and 10-day for TRB rules) returns (%) to following a buy-and-hold strategy.

Table 5
Results for technical trading rules in Latin American markets (%)

	MEX		BRA		ARG		CHI	
	MA	TRB	MA	TRB	MA	TRB	MA	TRB
(1,50,0)								
Buy	0.19	1.63	0.23	0.92	0.22	0.40	0.17	01.33
Sell	−0.09	−0.32	−0.19	−2.28	−0.26	−2.11	−0.10	−0.47
Buy−sell	0.29	1.96	0.43	3.19	0.48	2.51	0.28	1.80
p-value	0.05[c]	0.03[b]	0.00[a]	0.00[a]	0.45	0.11	0.06[c]	0.05[c]
(1,50,0.01)								
Buy	0.22	1.61	0.23	1.12	0.22	−0.19	0.20	1.22
Sell	−0.13	−0.13	−0.20	−1.99	−0.17	−0.38	−0.12	−0.56
Buy−sell	0.35	1.74	0.43	3.11	0.40	0.18	0.33	1.78
p-value	0.01[b]	0.07[c]	0.00[a]	0.00[a]	0.46	0.42	0.02[b]	0.06[c]
(1,150,0)								
Buy	0.12	1.30	0.12	0.51	0.01	2.42	0.10	1.47
Sell	−0.02	2.63	−0.05	−0.86	−0.05	1.60	−0.03	−0.79
Buy−sell	0.14	3.94	0.17	1.37	0.06	0.81	0.13	2.27
p-value	0.32	0.00[a]	0.12	0.15	0.90	0.30	0.27	0.06[c]
(1,150,0.01)								
Buy	0.12	1.48	0.12	0.54	0.03	1.98	0.11	1.51
Sell	−0.03	−3.95	−0.07	−1.20	−0.22	1.45	−0.03	−1.05
Buy−sell	0.15	5.43	0.19	1.73	0.06	0.53	0.14	2.57
p-value	0.28	0.00[a]	0.09[c]	0.12	0.92	0.36	0.29	0.05[c]
(5,150,0)								
Buy	0.10		0.04		−0.01		0.08	
Sell	0.02		−0.02		−0.02		−0.01	
Buy−sell	0.07		0.06		0.01		0.09	
p-value	0.33		0.30		0.60		0.16	
(5,150,0.01)								
Buy	0.11		0.05		0.01		0.08	
Sell	0.01		−0.02		−0.02		0.00	
Buy−sell	0.10		0.07		0.03		0.08	
p-value	0.20		0.30		0.57		0.24	
(1,200,0)								
Buy	0.10	1.15	0.08	1.10	0.09	2.29	0.10	1.63
Sell	0.01	−3.61	−0.03	−0.39	−0.07	1.64	−0.02	−0.61
Buy−sell	0.08	4.76	0.10	1.49	0.16	0.65	0.12	2.24
p-value	0.56	0.00[a]	0.35	0.16	0.48	0.31	0.25	0.09[c]
(1,200,0.01)								
Buy	0.09	1.51	0.07	1.41	0.04	3.10	0.10	1.79
Sell	0.01	−3.61	0.01	−0.13	−0.08	1.48	−0.02	−3.00
Buy−sell	0.08	5.13	0.06	1.55	0.17	1.62	0.13	4.79
p-value	0.57	0.00[a]	0.68	0.17	0.46	0.22	0.24	0.05[b]
Average	0.16	3.83	0.19	2.07	0.16	1.05	0.16	2.57
Buy-and-hold	0.08	0.77	0.05	0.46	0.03	0.30	0.04	0.44

Notes: VMA refers to Variable Length Moving Average rules, and TRB to Trading Range Break rules. Rules are defined as (S, L, B), where S is the length of the short moving average (represents nothing in the case of TRB rules), L is the length of the long moving average (represents the number of days over which maximum and minimum prices are calculated in the case of TRB rules), and B is the percentage band. Buy, sell, and buy−sell returns are daily averages (%) from following the buy and sell signals with a one-day lag over the whole sample period. The row labeled p-value is based on the buy−sell statistic of Brock et al. (1992), and reports the fraction of simulated statistics which are at least as large as the buy−sell statistic from the original series. [a], [b], and [c] denote significance at the 1, 5, and 10% levels, respectively. The row labeled Average reports the simple average of the buy−sell spread across all rules. The row labeled buy-and-hold reports average daily (and 10-day for TRB rules) returns (%) to following a buy-and-hold strategy.

Out of 64 VMA rules tested in all emerging markets (eight countries with eight strategies each), 35 strategies (i.e., 55% of the total number of rules) have buy returns significantly larger than sell returns at the 10% significance level.[19] All VMA models applied to Asian countries – excluding four rules in Thailand – produce significant buy–sell spreads which exceed by far the average unconditional one-day returns. This suggests that the evidence of predictability is not specific to the size or age of market studied. The Latin American markets account only for 7 (out of the 35) significant buy–sell differences (i.e., 20% of the total number of significant rules). Note that Argentina does not exhibit significant buy or sell returns at conventional levels.[20] On the whole, VMA rules uncover a higher degree of predictability in Asian than in Latin American markets, in agreement with Chang et al. (2003, 2004).[21]

It should also be noted that the (1,50,0) and (1,50,0.01) rules exhibit much higher returns compared with the other strategies in all markets, with the (1,50,0.01) rule yielding the largest return. In general, we observe that increasing the length of the long moving average, all else equal, reduces the buy–sell spread; increasing the length of the short moving average, all else constant, also causes a decline in buy–sell return. The introduction of the 1% bandwidth increases the buy–sell spread for the majority of VMA models. The analysis of the different technical rules therefore indicates that the rigorous selection of long moving average, short moving average, and bandwidth, can increase the potential profitability of the strategy even further.

As far as TRB rules are concerned, 34 out of a total of 48 rules (i.e., 71% of the total number of rules) identify significant buy–sell differences, again with Latin America exhibiting the smaller share (14 rules or 41% of the total significant TRB rules). Results confirm the significant predictability uncovered in Asian markets by VMA rules, apart perhaps from Thailand which exhibits only two significant buy–sell spreads. TRB results reinforce the previous finding of no predictability in the Argentinian market. On the contrary, significant predictability is uncovered in the Mexican and Chilean markets; in particular, the former market exhibits an average 10-day TRB rule buy–sell return only less to Taiwan's and Indonesia's. In agreement with VMA rule results, Indonesia is the most profitable market based on the TRB rules' average buy–sell return.

Taken together, 69 out of the 112 technical rules (62% of the total) produce buy signal returns which are not only positive, but also statistically different from the corresponding negative sell signal returns, demonstrating profit potential in emerging markets. Our results differ from those of Ratner and Leal (1999) who report that 22 rules out of the 100 tested in emerging markets demonstrate statistical significance. It should be noted that the latter authors employ a different sample of markets over an earlier time period, real instead of nominal returns, and a different set of trading rules.[22]

Tables 6 and 7 report the results of employing signals from VMA and TRB technical rules, respectively. The N(Buy) and N(Sell) rows refer to the number of buy and sell signals generated

[19] Chang et al. (2003, 2004) find a lower percentage of significant VMA rules (35%) at the 10% level; however, they additionally include India, Korea and Malaysia, and do not test VMA rules with a 1% band.

[20] This evidence is rather consistent with Urrutia (1995), who finds that the null hypothesis of a random walk in stock returns is rejected for Brazil, Chile, and Mexico, but not for Argentina.

[21] The reported trading rule evidence concurs with evidence from Cajueiro and Tabak (2004) who presented a rank of efficiency built by analyzing median Hurst exponents for different countries. The authors suggested that Asian equity returns are more inefficient than Latin American equity markets as the former possess greater median Hurst exponents.

[22] Ratner and Leal (1999) do not test TRB rules and use a band of one standard deviation for the VMA rules. Also, they do not include Indonesia in their sample, as we do, which produces significant returns across all rules tested.

Table 6
Excess returns from VMA rules

	PHI	TAI	THA	IND	MEX	BRA	ARG	CHI
(1,50,0)								
N(Buy)	1834	1653	1686	1810	2189	1873	1851	1878
N(Sell)	1722	1772	1799	1711	1359	1598	1697	1686
Annualized return (%)	47.9	43.9	54.0	65.2	38.1	51.9	46.9	34.8
Return less trading cost (%)	**38.6**	**34.4**	**46.1**	**58.3**	**27.4**	**39.9**	**36.1**	**25.3**
p-value	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.06[c]	0.00[a]	0.36	0.08[c]
(1,50,0.01)								
N(Buy)	1636	1483	1514	1657	2002	1709	1711	1670
N(Sell)	1523	1559	1657	1775	1193	1430	1430	1450
Annualized return (%)	48.0	44.0	54.2	70.7	41.5	46.9	43.6	36.0
Return less trading cost (%)	**39.2**	**33.6**	**45.4**	**63.4**	**31.2**	**35.3**	**31.6**	**27.2**
p-value	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.01[b]	0.00[a]	0.42	0.02[b]
(1,150,0)								
N(Trading)	43	67	89	62	89	68	111	73
N(Buy)	1629	1758	1702	1339	2275	1983	1788	1969
N(Sell)	1581	1724	1757	1684	1129	1581	1635	1514
Annualized return (%)	25.9	27.6	23.3	31.5	20.0	21.7	6.6	17.3
Return less trading cost (%)	**22.9**	**21.4**	**17.1**	**27.2**	**13.8**	**16.9**	**−1.1**	**12.2**
p-value	0.00[a]	0.02[b]	0.13	0.03[b]	0.43	0.14	0.94	0.30
(1,150,0.01)								
N(Buy)	1550	1680	1586	1254	2196	1919	1707	1841
N(Sell)	1511	1631	1654	1616	1052	1467	1538	1361
Annualized return (%)	24.7	26.5	22.5	31.9	21.0	23.1	6.3	16.5
Return less trading cost (%)	**21.2**	**21.3**	**16.9**	**28.1**	**15.4**	**17.9**	**−1.3**	**11.1**
p-value	0.04[c]	0.03[c]	0.15	0.05[c]	0.40	0.10[c]	0.95	0.29
(5,150,0)								
N(Buy)	1638	1738	1712	1346	2260	2001	1825	1791
N(Sell)	1580	1733	1776	1698	1146	1531	1637	1521
Annualized return (%)	22.0	22.4	14.5	27.6	13.0	8.2	1.5	11.1
Return less trading cost (%)	**19.7**	**19.4**	**10.4**	**24.8**	**9.2**	**4.9**	**−3.3**	**7.8**
p-value	0.02[b]	0.02[b]	0.15	0.01[a]	0.40	0.35	0.70	0.20
(5,150,0.01)								
N(Buy)	1567	1662	1592	1258	2199	1936	1745	1663
N(Sell)	1520	1648	1660	1611	1072	1481	1567	1381
Annualized return (%)	20.6	22.0	15.7	24.0	15.8	8.4	3.3	8.8
Return less trading cost (%)	**18.5**	**19.1**	**11.7**	**21.5**	**12.3**	**4.7**	**−1.4**	**5.1**
p-value	0.05[c]	0.02[b]	0.12	0.02[b]	0.24	0.46	0.70	0.30
(1,200,0)								
N(Buy)	1635	1760	1795	1291	2351	1955	1740	2043
N(Sell)	1561	1695	1664	1735	1014	1483	1659	1438
Annualized return (%)	20.3	24.0	20.6	34.3	14.7	13.0	19.2	16.1

(*continued on next page*)

Table 6 (*continued*)

	PHI	TAI	THA	IND	MEX	BRA	ARG	CHI
Return less trading cost (%)	**16.4**	**20.2**	**14.7**	**31.2**	**8.0**	**7.0**	**12.7**	**10.9**
p-value	0.04[b]	0.04[b]	0.10[c]	0.00[a]	0.60	0.40	0.55	0.35
(1,200,0.01)								
N(Buy)	1548	1697	1685	1192	2243	1894	1687	1928
N(Sell)	1491	1632	1552	1658	920	1407	1578	1313
Annualized return (%)	20.8	23.0	20.5	32.8	14.5	8.2	17.9	15.8
Return less trading cost (%)	**16.7**	**19.7**	**15.1**	**29.7**	**8.0**	**2.4**	**12.5**	**11.3**
p-value	0.04[b]	0.05[b]	0.11	0.00[a]	0.55	0.60	0.42	0.28

Notes: N(Buy) and N(Sell) are the number of buy and sell signals. The annualized return for each rule is the total buy−sell spread (considering the buy-and-hold strategy) over the whole sample period divided by the number of years in the sample. The "Return less trading cost" row is the annualized excess return considering the buy-and-hold strategy and transaction costs of 1% per trade. The row labeled p-value refers to the number of simulated returns net of trading costs which are at least as large as corresponding excess returns from the actual series.

by each rule. In Asian markets there is no strong, consistent evidence in favor of either bullish or bearish markets using buy and sell signals of VMA and TRB rules. This can be attributed to the high sensitivity of these markets to local, regional, and global events (Gunasekarage and Power, 2001). On the contrary, in Latin American markets N(Buy) exceeds N(Sell) across all rules, with clear evidence in favor of a primary upward trend in Mexico, and to a lesser extent, Brazil and Chile. This implies that it will be harder to "beat" the buy-and-hold benchmark in these countries.

The row labeled "Annualized return (%)" reports the annualized excess return (net of the buy-and-hold) from following the trading rule signals divided by the number of years in the sample (14(5/12)). It is clear that the trading strategies outperform the buy-and-hold, prior to transaction costs, in all markets, excluding only two TRB rules in Thailand. In general, and particularly for VMA rules, higher pre-trading cost returns are obtained in Asian markets compared to Latin American countries, as expected from the results reported in Tables 4 and 5. Indonesia exhibits the highest return among all markets for all VMA and TRB rules. There is a discernible pattern of pre-cost profitability among VMA and TRB rules, with the "faster" rules ((1,50,0) and (1,50,0.01)) exhibiting the highest returns. The average annualized return across all markets from VMA rules is 31.8% while for TRB rules it is 9.8%. This compares favorably with average annualized returns for the US market as reported by Brock et al. (1992), which were found to be, for example, about 19% for VMA rules.

The profitability of the various trading rules depends on the frequency of trades and associated transaction costs, which as discussed in Section 3.2, can be substantial in emerging markets. The "Return less trading cost (%)" row refers to average annualized excess returns for each trading rule net of the buy-and-hold and 1% cost per trade across all markets. In general, trading rules that emerge as statistically significant from Tables 4 and 5 seem to offer the highest excess returns after transaction costs. VMA rules appear consistently profitable and significant in Asian markets, offering larger returns than corresponding rules for Latin American markets. Although, in general, Latin American countries do enjoy positive returns after trading costs, these are statistically insignificant − excluding the (1,50,0) and (1,50,0.01) rule returns. Regarding all trading models tested (i.e., not considering statistical significance), the average annualized VMA rule excess return (net of trading costs) reaches 26.4% in Asian markets

Table 7
Excess returns from TRB rules

	PHI	TAI	THA	IND	MEX	BRA	ARG	CHI
(1,50,0)								
N(Buy)	81	83	80	85	108	93	90	88
N(Sell)	76	77	74	81	56	54	59	74
Annualized return (%)	19.4	19.8	13.1	30.1	13.5	14.4	11.1	10.5
Return less trading cost (%)	**8.5**	**8.7**	**2.4**	**18.6**	**2.1**	**4.3**	**0.8**	**−0.7**
p-value	0.05[b]	0.08[c]	0.12	0.00[a]	0.12	0.06[c]	0.20	0.15
(1,50,0.01)								
N(Buy)	64	66	67	64	87	78	69	70
N(Sell)	63	70	59	66	50	52	53	48
Annualized return (%)	18.0	16.0	6.9	29.2	10.2	13.2	0.5	7.8
Return less trading cost (%)	**9.2**	**6.6**	**0.0**	**20.2**	**0.1**	**4.2**	**−8.0**	**−0.4**
p-value	0.04[b]	0.10[c]	0.26	0.00[a]	0.18	0.07[c]	0.56	0.16
(1,150,0)								
N(Buy)	50	48	42	42	68	53	51	54
N(Sell)	40	40	41	40	16	24	37	32
Annualized return (%)	9.2	12.9	3.1	19.4	9.1	3.3	4.4	7.3
Return less trading cost (%)	**3.0**	**6.8**	**−2.7**	**13.7**	**3.2**	**−2.0**	**−1.7**	**1.3**
p-value	0.12	0.05[b]	0.26	0.04[b]	0.10[c]	0.24	0.43	0.16
(1,150,0.01)								
N(Buy)	38	38	35	30	57	40	38	42
N(Sell)	38	33	32	34	15	21	33	19
Annualized return (%)	5.2	11.6	−2.0	21.0	10.0	3.2	1.9	5.8
Return less trading cost (%)	**0.0**	**6.7**	**−6.6**	**16.6**	**5.0**	**−1.0**	**−3.0**	**1.6**
p-value	0.28	0.02[b]	0.92	0.00[a]	0.02[b]	0.58	0.32	0.16
(1,200,0)								
N(Buy)	41	41	34	33	66	46	41	43
N(Sell)	35	33	37	35	12	20	30	25
Annualized return (%)	9.1	9.4	4.3	16.0	8.3	4.0	3.1	5.9
Return less trading cost (%)	**3.8**	**4.2**	**−0.1**	**11.3**	**2.9**	**−0.5**	**−1.8**	**1.2**
p-value	0.07[c]	0.06[c]	0.14	0.02[b]	0.12	0.26	0.51	0.16
(1,200,0.01)								
N(Buy)	30	31	29	25	55	35	29	36
N(Sell)	34	29	29	31	12	17	27	13
Annualized return (%)	7.2	6.7	−0.4	16.4	8.8	3.6	3.5	7.2
Return less trading cost (%)	**2.8**	**2.6**	**−4.4**	**12.5**	**4.1**	**0.0**	**−0.4**	**3.8**
p-value	0.09[c]	0.14	0.72	0.04[b]	0.01[a]	0.32	0.40	0.05[c]

Notes: N(Buy) and N(Sell) are the number of buy and sell signals generated by each rule. The annualized return for each rule is the total buy−sell spread (considering the buy-and-hold strategy) over the whole sample period divided by the number of years in the sample. The "Return less trading cost" row is the annualized excess return considering the buy-and-hold strategy and transaction costs of 1% per trade. The row labeled p-value refers to the number of simulated returns net of trading costs which are at least as large as corresponding excess returns from the actual series. [a], [b], and [c] denote significance at the 1, 5, and 10% levels, respectively.

compared with 14.1% in Latin America. The average annualized VMA rule excess return across all markets of 20.3% is almost three times as big as the average VMA rule annualized excess return (net of trading costs and the nonsynchronous trading correction) of 6.31% for the US reported by Bessembinder and Chan (1998) between 1926 and 1991.

On the contrary, TRB rules do not allow for profits as large as those observed for VMA rules, with excess returns considerably eroded by the application of 1% transaction cost. The latter result is mainly because of the construction of the TRB rules, which, due to the fixed 10-day holding period, have much fewer buy and sell signals than corresponding VMA rules, being, in addition, more trade-intensive. Again, Asian markets are more profitable than Latin American markets: Disregarding statistical significance, the average annualized excess return after transaction costs is 6.0% in Asian countries and 0.6% in the Latin American countries, an average across all markets of 3.3%.[23] It should be noted that Indonesia remains the most profitable market after transaction costs across TRB strategies as well.

Finally, it is important to characterize the level of risk at which excess returns are obtainable before deciding whether it is worthwhile for investors to pursue such strategies in ECM. Table 8 presents the annualized Sharpe ratios that investors can achieve with VMA rules after considering the buy-and-hold strategy and transaction costs.[24] The Sharpe ratios attained with technical trading rules present a considerable improvement over those achieved with the buy-and-hold strategy in the respective countries: It is evident that Sharpe ratios are highly significant across all rules in Asian markets as well as in Chile, and significant for most rules in the other Latin American countries, implying that trading rule excess returns do not come at the expense of higher risk compared to the buy-and-hold. Moreover, despite the fact that VMA rules do not offer as high profit levels in Latin America as they do in Asia, it is still beneficial for investors to pursue such strategies in Latin America. What's more to the purpose, from the point of view of a US investor, is that the Sharpe ratio for an aggregate US equity portfolio buy-and-hold strategy ranges from 0.3 to 0.4 (LeBaron, 2002). Furthermore, Sullivan et al. (1999) report that the Sharpe ratio for the buy-and-hold strategy on the Dow Jones Industrial Average over 100 years (1897–1996) is a mere 0.034, whereas the best performing trading rule produces a Sharpe ratio of 0.82. The (statistically significant) Sharpe ratios we find for ECM range between 0.5 and 3.5 and largely exceed the aforementioned benchmark values for the US market.

5.4. Model-based bootstrap results

Tables 9 and 10 summarize results across all rules using a simple average: The "Simulation mean" row refers to the returns and standard deviations for buy signals, sell signals, and buy–sell spreads, averaged over the 500 simulated series for each market. These can be compared with the corresponding statistics from the actual index series, providing a model-based simulated p-value (for the average rule results). The i.i.d. bootstrapped p-value (for the average rule statistics) is also provided for comparison.

For the Asian markets, the VMA rules average buy–sell model-based p-values indicate that the underlying statistical returns model cannot be rejected at the 5% significance level in the

[23] Bessembinder and Chan (1998) report an average annualized excess return of −0.13% for TRB rules in the US market.

[24] We only present Sharpe ratios for VMA rules which were found to be more profitable. Results for TRB rules are available at request.

Table 8
Annualized Sharpe ratios for VMA rules

	PHI	TAI	THA	IND	MEX	BRA	ARG	CHI
(1,50,0)	3.141[a]	2.381[a]	2.935[a]	2.720[a]	1.853[a]	2.016[a]	1.449[a]	2.893[a]
(1,50,0.01)	3.549[a]	2.660[a]	3.184[a]	2.941[a]	2.357[a]	1.985[a]	1.472[a]	3.468[a]
(1,150,0)	1.857[a]	1.416[a]	1.099[a]	1.505[a]	0.760[a]	0.711[b]	0.034	1.231[a]
(1,150,0.01)	1.826[a]	1.443[a]	1.140[a]	1.589[a]	0.879[a]	0.828[a]	0.027	1.238[a]
(5,150,0)	1.556[a]	1.176[a]	0.607[a]	1.308[a]	0.281	0.173	−0.098	0.755[a]
(5,150,0.01)	1.518[a]	1.210[a]	0.740[a]	1.189[a]	0.508[b]	0.175	−0.037	0.532[a]
(1,200,0)	1.384[a]	1.267[a]	0.958[a]	1.675[a]	0.279	0.331	0.469[a]	1.058[a]
(1,200,0.01)	1.486[a]	1.263[a]	1.039[a]	1.660[a]	0.290	0.097	0.521[a]	1.134[a]
Buy-and-hold	−0.131	−0.004	−0.177	−0.084	0.462	0.147	0.042	0.302

Notes: The annualized Sharpe ratio for each trading rule is based on annualized excess returns (considering the buy-and-hold strategy and transaction costs) less the risk-free interest rate. [a], [b], and [c] denote significance at the 1, 5, and 10% levels, respectively; significance is measured as the number of simulated Sharpe ratios for each trading rule which are at least as large as the corresponding Sharpe ratios in the actual data.

Philippines, Thailand, and Indonesia, and at the 1% level in Taiwan, and buy returns are generally better replicated by the simulated models than sell returns.[25] Our finding is consistent with evidence from Edwards et al. (2003) regarding the ability of "simple" returns processes to capture bull phases in emerging markets more adequately than bear phases. Furthermore, the simulated models do a good job in tracking both buy and sell volatilities. In particular, the buy return standard deviations are better replicated than corresponding sell volatilities in Taiwan, Thailand, and Indonesia, as indicated by the p-values, and also by the fact that average simulated buy return volatilities are closer to their actual values than simulated sell volatilities are to their corresponding values from the actual index series.

In Latin American markets the simulated models replicate quite successfully conditional mean and volatility dynamics across all rules, with p-values much higher than conventional significance levels. A simple comparison of actual and simulated VMA rule averages suggests that trading rule statistics are not different from those of market index data. Moreover, buy and sell returns are equally well explained by the statistical processes, apart perhaps from Chile where sell returns (average p-value 0.668) appear to be better replicated than buy returns (average p-value 0.092). Similarly to Asian markets, sell signals select periods of lower return and higher volatility than buy signals do. In addition, the simulated models in Latin American markets produce a spread between buy and sell volatilities in favor of the latter, consistent with actual data.

Table 10 shows that for the average TRB rule, model-based bootstrap tests cannot reject the null hypothesis of equal buy−sell returns in actual and simulated data at the 1% level in all markets except Taiwan. The simulated AR(2)−FIGARCH(1,δ,0) process in Thailand seems to fit the TRB rule returns even better than the VMA returns. In contrast with VMA rule results, average buy−sell spreads are "significant" at the 5% level in Mexico and Chile.[26] For Argentina and Brazil, inferences from TRB rule bootstrap returns agree with VMA results. As with

[25] Hatgioannides and Mesomeris (2003) also investigate the significance of the individual trading rule returns and volatilities relative to the simulated model for each market. Their results reinforce the above findings.

[26] However, Hatgioannides and Mesomeris (2003) find that individual rule buy and sell returns are rather well replicated by the simulated series, particularly for Mexico.

Table 9
Simulation tests for VMA rules averages (%)

	Buy	Buy stdev	Sell	Sell stdev	Buy−sell
Actual PHI mean	0.11	1.41	−0.15	2.08	0.26
Simulation mean	0.07	2.24	−0.06	2.15	0.13
Model-based *p*-value	0.17	0.88	0.92	0.34	0.06
IID *p*-value	0.03	1.00	1.00	0.00	0.00
Actual TAI mean	0.13	1.88	−0.12	2.41	0.25
Simulation mean	0.08	1.91	−0.05	1.95	0.13
Model-based *p*-value	0.09	0.44	0.94	0.08	0.03
IID *p*-value	0.07	1.00	0.98	0.00	0.01
Actual THA mean	0.10	0.02	−0.14	2.58	0.24
Simulation mean	0.05	0.02	−0.09	1.95	0.13
Model-based *p*-value	0.12	0.48	0.86	0.12	0.07
IID *p*-value	0.13	1.00	0.98	0.00	0.01
Actual IND mean	0.14	2.06	−0.21	3.53	0.35
Simulation mean	0.06	2.47	−0.09	2.34	0.11
Model-based *p*-value	0.09	0.42	0.94	0.10	0.05
IID *p*-value	0.08	1.00	1.00	0.00	0.00
Actual MEX mean	0.13	1.50	−0.03	2.59	0.16
Simulation mean	0.14	1.78	0.01	2.13	0.13
Model-based *p*-value	0.58	0.78	0.73	0.13	0.30
IID *p*-value	0.07	1.00	0.40	0.00	0.19
Actual BRA mean	0.12	2.49	−0.07	3.35	0.19
Simulation mean	0.17	3.44	−0.12	4.44	0.29
Model-based *p*-value	0.63	0.57	0.58	0.47	0.45
IID *p*-value	0.12	0.00	0.74	0.00	0.08
Actual ARG mean	0.08	3.78	−0.07	3.93	0.16
Simulation mean	0.08	4.85	−0.18	5.73	0.26
Model-based *p*-value	0.46	0.46	0.30	0.57	0.65
IID *p*-value	0.74	0.41	0.53	0.37	0.65
Actual CHI mean	0.12	1.21	−0.04	1.28	0.16
Simulation mean	0.07	1.55	−0.02	1.66	0.09
Model-based *p*-value	0.09	0.74	0.69	0.67	0.11
IID *p*-value	0.08	1.00	0.63	1.00	0.10

Notes: The table presents results for the averages across all the VMA rules for each reported trading rule statistic. The actual and simulated (model-based) mean return and mean standard deviation across all rules is reported. The row labeled "model-based *p*-value" reports the fraction of simulations – generated using the specified econometric model for each market – yielding a statistic (simulated average across rules) at least as large as that of the original series in each market. The row labeled "IID *p*-value" is similarly constructed but based on i.i.d bootstrapped statistics.

VMA rules, the volatility dynamics of TRB rule returns in all markets are adequately explained by the simulations – the lowest *p*-value being 0.940 for the buy return volatility in Mexico – providing robust evidence for the success of the FIGARCH volatility process.

Overall, the lower predictive performance of technical trading rules in Latin American as opposed to Asian markets – confirmed with the model-based bootstrap as well – may be a natural consequence of the more extensive financial liberalization process the Latin American countries have undergone, leading to openness and efficiency of asset prices, as well as the profound influence of the Asian crisis on Asian markets (see Edwards et al., 2003).

Table 10
Simulation tests for TRB rules averages (%)

	Buy	Buy stdev	Sell	Sell stdev	Buy−sell
Actual PHI mean	1.97	5.67	−0.0127	7.43	3.24
Simulation mean	0.14	9.37	−0.0000	9.22	0.14
Model-based *p*-value	0.07	0.81	0.83	0.51	0.07
IID *p*-value	0.00	0.35	0.98	0.01	0.00
Actual TAI mean	1.43	6.58	−2.42	8.68	3.85
Simulation mean	0.40	7.10	−0.09	7.37	0.49
Model-based *p*-value	0.12	0.56	0.98	0.17	0.01
IID *p*-value	0.05	0.61	1.00	0.01	0.00
Actual THA mean	1.34	5.40	0.39	9.86	0.95
Simulation mean	−0.17	9.27	−0.68	8.37	0.50
Model-based *p*-value	0.17	0.92	0.15	0.20	0.40
IID *p*-value	0.05	0.99	0.33	0.00	0.23
Actual IND mean	5.23	15.08	−2.11	12.22	7.34
Simulation mean	−0.03	12.86	−0.48	11.57	0.45
Model-based *p*-value	0.03	0.22	0.87	0.26	0.02
IID *p*-value	0.00	0.00	0.96	0.04	0.00
Actual MEX mean	1.45	5.34	−2.38	12.75	3.83
Simulation mean	1.00	7.05	0.70	9.31	0.30
Model-based *p*-value	0.26	0.94	0.94	0.12	0.03
IID *p*-value	0.04	0.96	1.00	0.00	0.00
Actual BRA mean	0.93	9.98	−1.14	14.99	2.07
Simulation mean	0.43	11.83	−0.01	17.70	0.45
Model-based *p*-value	0.36	49.8	0.71	0.40	0.26
IID *p*-value	0.18	0.00	0.95	0.00	0.02
Actual ARG mean	1.66	14.94	0.61	12.47	1.05
Simulation mean	−0.70	19.22	−0.99	23.23	0.29
Model-based *p*-value	0.13	0.52	0.29	0.83	0.38
IID *p*-value	0.15	0.21	0.74	0.39	0.24
Actual CHI mean	1.49	5.47	−1.08	6.78	2.57
Simulation mean	0.19	7.00	0.37	7.56	−0.17
Model-based *p*-value	0.08	0.66	0.89	0.44	0.05
IID *p*-value	0.05	0.99	0.92	0.44	0.02

Notes: The table presents results for the averages across all the TRB rules for each reported trading rule statistic. The actual and simulated (model-based) mean return and mean standard deviation across all rules is reported. The row labeled "model-based *p*-value" reports the fraction of simulations − generated using the specified econometric model for each market − yielding a statistic (simulated average across rules) at least as large as that of the original series in each market. The row labeled "IID *p*-value" is similarly constructed but based on i.i.d bootstrapped statistics.

5.5. Effects of the Asian crisis

In this paper, we have taken the view that *ex post* documented episodes of financial market crises are parts of the same generating process for stock returns rather than a shift to a new regime. However, due to the profound influence of the Asian crisis on the Asian ECM, it is worthwhile to investigate whether the forecasting ability of trading rules in Asian stock markets is driven by the sizeable (negative) return outliers observed during the period of the crisis. Using the VMA strategies, which produce a much larger number of signals than corresponding TRB rules, we report subsample VMA rule returns before and after the crisis for Asian ECM.[27] The Asian crisis period is identified as: July 2, 1997–September 30, 1998 for Thailand, July 11, 1997–September 30, 1998 for Philippines, August 4, 1997–October 6, 1998 for Indonesia, October 17, 1997–September 30, 1998 for Taiwan (see Kamesaka and Wang, 2003). The start dates of the crisis in each country correspond to the currency floating dates. Results appear in Table 11 and can be compared with VMA results for the full sample from Table 4.[28]

The general conclusion is that the degree of forecasting power has decreased in Asian economies over time, as the number of significant buy–sell returns has declined from 50% for before the crisis to 13% for the more recent subsample. Apart from Indonesia, the average buy–sell return across all VMA rules declined in the second subsample as well. These results are in line with Chang et al. (2003, 2004) and may signal that a transition to a developed market, "efficient-type" status took place after the crisis for the Asian ECM studied in this paper.

It is interesting though that buy–sell returns from the most profitable – over both the full sample and individual subsamples – of the VMA trading rules, namely the (1,50,0) and (1,50,0.01) strategies, remain statistically significant in the post-crisis period. Furthermore, it is worth noting that for Philippines, Thailand, and Indonesia, the shorter-length rules show higher buy–sell returns in the second subsample compared to the first (and to the full-sample results in the case of Indonesia and Thailand). On balance, our results suggest that the drop in predictability after the Asian crisis is confined to the longer-length rules whereas there is no evidence of a "structural break" in the performance and significance of the "best" – in terms of profitability – VMA strategies.

Finally, the average buy–sell spread in the two subsamples is closer to the full-sample average in Taiwan rather than in the other Asian markets. This is because the stock market and exchange rate of Taiwan were affected to a lesser degree than those of other Asian countries during the turmoil; though the MSCI Taiwan index dropped by about 34% in US dollar terms, it compares favorably with US dollar drops of around 70% for the MSCI Philippines, 75% for the MSCI Thailand, and 93% for the MSCI Indonesia indices.

6. Conclusion

In this paper we have carried out a comprehensive study of the returns generating process and profitability of relatively simple and well known to traders technical rules in ECM, notably four Asian and four Latin American countries. Using daily data since 1988 for all countries, we have provided evidence that the dollar denominated returns generating process exhibits statistically significant long-memory effects in the volatility but not in the mean. "Trading" upon such findings, we concluded that VMA and TRB rules outperform the simple "buy-and-hold" strategy for all markets before transaction costs. Predominantly in Asian markets the profitability of the trading rules is sustained even after transaction costs are taken into consideration.

[27] We have also experimented with the performance of the VMA trading rules when the period of the Asian crisis is excluded from the full sample. Results are available upon request.

[28] In our subsample analysis, we ignore the signals and subsequent returns of VMA rules that have occurred throughout the period of the crisis. Thus, we have a clearer assessment of the rules' performance "before" and "after" the crisis. This is in contrast with the subsample analysis conducted by Chang et al. (2003, 2004) who somewhat arbitrarily split their sample at December 1997 for all Asian ECM.

Table 11
Results for VMA rules in Asian markets before and after the Asian crisis (%)

	PHI		TAI		THA		IND	
	Before	After	Before	After	Before	After	Before	After
(1,50,0)								
Buy	0.19	0.19	0.20	0.17	0.18	0.28	0.25	0.48
Sell	−0.12	−0.19	−0.18	−0.15	−0.18	−0.19	−0.13	−0.20
Buy−sell	0.31[a]	0.37[a]	0.38[a]	0.32[b]	0.36[a]	0.47[a]	0.38[a]	0.68[a]
(1,50,0.01)								
Buy	0.22	0.27	0.24	0.19	0.21	0.29	0.24	0.46
Sell	−0.15	−0.17	−0.21	−0.14	−0.19	−0.22	−0.20	−0.22
Buy−sell	0.37[a]	0.44[a]	0.45[a]	0.33[b]	0.39[a]	0.51[a]	0.44[a]	0.68[a]
(1,150,0)								
Buy	0.13	0.05	0.13	0.09	0.08	0.10	0.05	0.19
Sell	−0.08	−0.07	−0.10	−0.11	−0.08	−0.02	−0.08	0.02
Buy−sell	0.21[a]	0.12	0.23[a]	0.20	0.16	0.12	0.13	0.18
(1,150,0.01)								
Buy	0.12	0.04	0.12	0.09	0.09	0.09	0.06	0.17
Sell	−0.08	−0.06	−0.11	−0.12	−0.08	−0.02	−0.10	0.02
Buy−sell	0.20[a]	0.10	0.23[a]	0.21	0.18	0.11	0.16[c]	0.15
(5,150,0)								
Buy	0.11	0.03	0.11	0.10	0.06	0.03	0.04	0.16
Sell	−0.04	−0.06	−0.07	−0.10	−0.03	0.01	−0.07	0.07
Buy−sell	0.15[b]	0.09	0.18[c]	0.20	0.09	0.02	0.11	0.09
(5,150,0.01)								
Buy	0.11	0.01	0.11	0.10	0.07	0.04	0.05	0.16
Sell	−0.02	−0.07	−0.07	−0.10	−0.05	0.01	−0.05	0.15
Buy−sell	0.13[c]	0.08	0.18[c]	0.20	0.12[c]	0.03	0.10	0.02
(1,200,0)								
Buy	0.08	−0.02	0.10	0.06	0.06	0.07	0.07	0.22
Sell	−0.06	−0.05	−0.09	−0.12	−0.06	0.00	−0.13	0.00
Buy−sell	0.15[b]	0.03	0.19[b]	0.18	0.13	0.07	0.20[a]	0.22
(1,200,0.01)								
Buy	0.08	−0.02	0.10	0.06	0.08	0.04	0.06	0.23
Sell	−0.06	−0.05	−0.08	−0.11	−0.07	0.00	−0.13	0.00
Buy−sell	0.15[c]	0.03	0.18[c]	0.18	0.15	0.04	0.19[b]	0.24
Average	0.21	0.16	0.25	0.23	0.20	0.17	0.21	0.28

Notes: Buy, sell, and buy−sell returns are as defined in Tables 4 and 5, but based on data before and after the Asian crisis, respectively. The periods excluded from the analysis are as follows: July 2, 1997−September 30, 1998 for Thailand, July 11, 1997−September 30, 1998 for Philippines, August 4, 1997−October 6, 1998 for Indonesia, and October 17, 1997−September 30, 1998 for Taiwan. The last row is the average buy−sell spread across the eight VMA rules. [a], [b], and [c] denote significance at the 1, 5, and 10% levels, respectively (based on i.i.d. bootstrapped *p*-values).

Suggestions of possible data-snooping biases in our trading results are partially removed with the use of a data set that was previously relatively unexplored in the academic literature and by reporting results from all rules. Model-based bootstrap simulations reveal that the ‘‘favorite’’ stochastic process for the generation of returns in ECM can reproduce technical trading rule results, particularly for VMA strategies in Latin American countries that are consistent with those from the actual data series.

The robustness of our results is further reinforced by: First, predictability in ECM cannot be attributed to nonsynchronous measurement biases. Second, Sharpe ratios that foreign investors can achieve with VMA rules after considering the buy-and-hold benchmark strategy and transaction costs are highly significant across all Asian markets as well as in Chile, and significant for most rules in the other Latin American countries. Furthermore, both excess returns and Sharpe ratios compare favorably with results reported for US studies. Third, the significant forecasting performance of the most profitable VMA strategies in the Asian ECM is unaffected by the Asian crisis.

All in all, our results cast serious doubt on the weak form efficiency of ECM economies. It would be interesting for future research to investigate whether the investment flow by foreigners in ECM significantly affects the returns generating process. The latter could be done, for instance, by including the dollar amount of net daily trades by foreigners as an independent variable in the statistical model of returns. At present, the lack of a sufficiently long data series for such trades does not allow us to carry out such a task.

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