On The Returns Generating Process And The Profitability Of Trading Rules In Emerging Capital Markets

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Abstract

This article investigates the returns generating process and profitability of popular trading rules in four Asian and four Latin American markes using daily MSCI index data since 1988. We find that dollar denominated returns exhibit significant long memory effects in the volatility but not in the mean, which is consistent with the higher returns generated by the shortest-length rules. We find that moving average and trading range break rules outperform the simple "buy-and-hold" strategy, and that it is possible to generate significant excess returns with some of the trading rules in Asian markets even after allowing for transaction costs, in contrast with the Latin American markets. The significance of our results is reinforced by bootstrap simulations of the underlying returns process.

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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. Notwithstanding their high risk, the higher sample average returns and the low correlations with developed market returns are two of the distinguishing features of emerging capital market returns (Bekaert and Harvey, (1997)) that have made such markets increasingly attractive to international investors.[1] Such characteristics, coupled with the financial liberalization process these countries have embarked on,[2] 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)).[3]

Despite the significance of ECM as important conduits of international diversification, little has been said in the literature about the 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

[1] De Santis (1993) and Harvey (1995) find significant diversification benefits for emerging market investments using International Finance Corporation (IFC) indexes which, however, do not account for the high transaction costs, low liquidity, and investment constraints associated with emerging market investments. Bekaert and Urias (1996, 1999) measure diversification benefits using data on closed-end funds and American Depository Receipts (ADRs) which are easily accessible to retail investors and have comparable transaction costs to those of U.S. traded stocks. They find that, in general, investors give up a substantial part of their diversification benefits by holding closed-end funds; on the contrary, open-end funds which track the IFC indices much better than alternative investment vehicles prove to be the best diversification instrument. De Roon at al (2001) and Li et al (2003) employ IFC indices and take transaction costs directly into account when measuring diversification benefits. The former authors find that diversification benefits of investing in emerging markets are eliminated when transaction costs, and, in particular, short-sale constraints are introduced. However, they admit that there is evidence of some bias in their asymptotic spanning analysis. On the contrary, Li et al (2003), using a Bayesian approach that incorporates the uncertainty associated with finite samples, argue that diversification benefits remain substantial even in the presence of short-sale constraints.

[2] At the start of our sample (1988), 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 in our sample opened up to foreign investment far earlier and far more extensively than their Asian counterparts; 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.

[3] For example, using data from 16 emerging markets, Bekaert and Harvey (2003) show that the U.S. share of market capitalization has almost doubled in the 1990s compared with the 1980s, whereas in dollar terms, U.S. holdings have increased 10-fold in the 5-years post-liberalization versus the 5-years pre-liberalization. The liberalization date for each market is the Official Liberalization Date from Bekaert and Harvey (2000).

well as higher persistence in stock returns; Bekaert (1995), Bekaert and Harvey (1995), and Harvey (1995a,b)) report statistically significant sample autocorrelations in emerging market returns. 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. As noted by Wright (1999), persistence in equity returns of ECM could potentially reflect a lack of liquidity, though Harvey (1995b) argues against this possibility.[4]

Persistence in equity returns may be attributed to long range dependence, or long memory, in the returns time series. 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. Also, "learning effects" are bound to be important; investors in ECM tend to react slowly and gradually to new information (Barkoulas et al (2000)). In addition, the mounting evidence of nonnormality and nonlinearities in ECM returns (see, for example, Harvey (1995a), Bekaert and Harvey (1997), Alford and Lussier (1996)), is consistent with a persistent (either in mean and/or volatility) return generating process in emerging markets.

Such characteristics of a market suggest that technical trading rules could be profitable.[5] One such class of rules is the moving average rule, which has been frequently used for forecasting and recommending strategies by technical trading analysts with the objective of maximizing profit and minimizing the risk of loss. Series which are long-term dependent exhibit "trends" and "cycles" of varying lengths (Mandelbrot (1972)). 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. A significant long memory component in the conditional mean of security returns would render high-order moving average rules profitable and recommendable; otherwise, if a price series only possesses short memory, a low-order moving average rule can be recommended.

The value added of technical analysis lies not only in identifying profitable trading opportunities, but also in uncovering hidden patterns in stock returns not picked up by standard statistical tests, which can help to better forecast prices. Moreover, technical analysis can shed light on whether predictable variation in equity returns (which renders technical analysis useful) is a result of market inefficiency or can be attributed to time-varying equilibrium risk pre-

[4] Urrutia (1995) is skeptical about the interpretation of autocorrelation in emerging markets, and offers another explanation. Since both the economy and the capital markets of developing economies are growing at unusually fast rates, it is possible that autocorrelations are indicators of economic growth rather than evidence against the efficient market hypothesis.

[5] Van Der Hart et al (2003) examine the profitability of a broad range of stock selection strategies by studying 3000 securities in 32 emerging markets over the period 1985-1999. They find that value and momentum strategies generate significant excess returns, in contrast to strategies based on size and mean reversion, even after accounting for low liquidity, outliers in stock returns, an implementation delay, and transaction costs faced by large institutional investors. They confirm the profitability of such strategies cannot be explained by traditional asset pricing models, and do not find a pronounced effect of financial market liberalization on the performance of the strategies.

mia.[6]

Although such investigations and issues have been partly addressed in the case of developed markets (see, for example, Brock et al (1992) and Sullivan et al (1999) for the US, Hudson et al (1996) for the UK), there has been, to the best of our knowledge, no extensive study of this sort regarding ECM. In this paper, we test moving average and trading range break strategies in eight countries belonging to two geographical regions, Asia (Philippines, Taiwan, Thailand, Indonesia) and Latin America (Mexico, Brazil, Argentina, Chile).[7] A mix of different exchanges is included in this sample; the stock markets examined vary in age, size, and spread of securities traded. Therefore, the findings of this paper may provide some evidence about the influence of the different exchange characteristics on the results. Moreover, it would be interesting to compare results across regions, given that Latin American markets have been more "open" over the sample period compared to their Asian counterparts (see footnote 2).

Our methodology follows the studies by Brock et al (1992), Levich and Thomas (1993), Osler and Chang (1995) and Sullivan et al (1999), as standard statistical tests are augmented by the bootstrap methodology to carry out statistical inferences on trading rule profitability and ability to forecast future price changes. However, our study differs in that, motivated by the existing literature on the empirical regularities of stock return dynamics and the widely documented characteristics of ECM returns, we first search for an appropriate model for the return generating process in each market among the double long-memory ARFIMA-FIGARCH class of models.

Having decided on the "best" model and appropriate simulation technique via rigorous econometric tests, we conduct bootstrap simulations of the underlying returns process using the estimated parameters for the fitted model and apply our trading rules in each of the simulated series. The statistical significance of the trading rule results are assessed by direct comparison to the results from the simulated series.

The remainder of this paper is organized as follows: In Section 2 we present the econometric model and its motivation. Section 3 presents the data set, econometric methodology, trading rules and bootstrap procedures. Section 4 addresses the empirical results and discusses their significance. Section 5 concludes the paper.

[6] Predictability of returns over short horizons can also be due to market microstucture effects. Reversals in recorded returns can be accounted for by movements from the bid to the ask. Since our trading strategies are not based on return reversals, this microstructure explanation is implausible.

[7] Gunasekarage and Power (2001) apply moving average rules in the context of four South Asian stock markets, Bangladesh, India, Pakistan, and Sri Lanka, using daily index data from 1 January 1990 to 31 March 2000. Parisi and Vasquez (2000) test moving average and trading range break-out rules using daily data from 1987 to 1998. Both studies provide strong support for technical strategies in these markets.

2 The Econometric Model

2.1 Motivation

The dynamic behavior of stock prices and conditional volatility has been the focus of many empirical studies in the financial literature. Characterizing the returns generating mechanism is a crucial issue for asset and risk management, asset pricing and portfolio allocation. Conditional second moments play a key role in portfolio diversification and risk hedging strategies, which rely on the ability to predict variances and covariances. Many asset pricing models postulate that the expected return on any asset depends on its covariance with the pricing factors. Volatility is also an input in derivative pricing models. As De Santis and Imrohoroğlu (1997) note, although most emerging markets still lack sophisticated financial instruments, characterizing the distribution and dynamics of stock prices is a first necessary step towards their development.

Contrary to the random walk hypothesis, several studies find evidence of long horizon predictability in stock returns (Fama and French (1988), Poterba and Summers (1988), Mills (1993) inter alia). Lo (1991) argues that such evidence may be symptomatic of a long-range dependent (long-memory) component in stock market prices, allowing asset returns to exhibit significant autocorrelation between distant observations.[8] Consequently, many authors have tested for long memory in asset returns, but thankfully for the proponents of the market efficiency hypothesis, met with little success.[9] Two interesting exceptions are the studies by Barkoulas et al (2000) and Wright (1999, 2001), which find evidence of long memory in some emerging market returns using the Geweke and Porter-Hudak (1983) spectral regression method. These findings suggest the possibility

[8] The presence of long memory contradicts the weak form of the efficient market hypothesis; if the series realizations are not independent over time, then past returns can help predict future returns, giving rise to consistent speculative profits that can be exploited via appropriate trading rules. Also, optimal consumption/savings and portfolio decisions may become sensitive to the investment horizon if stock returns were long-range dependent. If financial time series exhibit long memory, then their unconditional probability distributions may not be normal. This has important implications for many areas in finance, especially asset and option pricing, portfolio allocation and risk management. Moreover, Mandelbrot (1971) observes that in the presence of long memory the arrival of new market information is not fully arbitraged away and martingale models of asset prices cannot be obtained from arbitrage. Thus pricing derivative securities with martingale methods may be inappropriate if the underlying stochastic process exhibits long memory.

[9] For example, Lo (1991) finds no evidence of long memory in U.S. stock returns (equal- and value-weighted CSRP indexes) using the modified R/S method, which robustifies the rescaled range statistic of Hurst (1951) against short run dependence. Cheung and Lai (1995) find no evidence of persistence in several international stock returns series using both the modified R/S method and the spectral regression method of Geweke and Porter-Hudak (1983). Crato (1994) reports similar evidence for the stock returns series of the G-7 countries using exact maximum likelihood estimation. Lobato and Savin (1998) use a semiparametric procedure to find no evidence of long memory in the level of the returns of the S&P 500 index (between July 1962 and December 1994) and in the returns of the stocks comprising the Dow Jones Industrial Average. Jacobsen (1996) tested for long memory in U.S., Japanese, and Western European stock index returns, Hiemstra and Jones (1997) considered long memory in U.S. individual stock returns, whereas Cheung (1993) tested for long memory in exchange rate returns, all with little evidence of long memory.

of differential long-term stochastic behavior between major and emerging capital markets, inviting a more thorough examination of stock return dynamics in smaller and less developed stock markets.

In contrast with findings of little serial correlation in asset prices returns, asset prices volatilities seem to exhibit a much richer structure. There is a lot of evidence that conditional volatility of asset returns (proxied by squared, log-squared, or absolute returns) displays long memory or long range dependence (see, for example, Taylor (1986), Ding et al (1993), Granger and Ding (1995), Ding and Granger (1996), Dacorogna et al (1993), de Lima and Crato (1994), Psaradakis and Sola (1995), Bollerslev and Mikkelsen (1996), and Lobato and Savin (1998)). It is possible that such findings are "contaminated" by the presence of structural breaks in the return volatlity process.[10] However, the debate is still far from settled. Lobato and Savin (1998) and Baillie (1998) find little evidence of significantly time-varying long memory in long time series of the S&P500 index. Baillie points out that the pre-war and post-1987 periods appear to be characterized by very large outliers (which raise the mean of squared returns) rather than by any fundamental change in the persistence of the volatility process. Moreover, the estimates of the long memory conditional variance parameter appear quite robust to changes in the specification of the conditional mean. Baillie et al (2000) provide evidence that the long memory property is an intrinsic feature of the Deutchmark-US dollar spot exchange rate system rather than being due to exogenous shocks which lead to regime shifts. This is consistent with the theory that returns are a self similar process (see Beran (1994)). Andersen and Bollerslev ((1997), (1998)) provide evidence that the long memory characteristic of the volatility process "constitute an intrinsic feature of the returns generating process, rather than a manifestation of occasional structural shifts" (Andersen and Bollerslev (1997), page 975).

Consistent with these and other studies, we regard episodes of financial market crisis as being part of the same generating process for stock returns, rather than signaling a shift to a new regime. For this reason we resist including dummy variables or any other mechanism of inducing a "better fit" to the sample period. If structural breaks are indeed considered as exogenous, resulting in ill-conditioning of the volatility processes distribution, then that problem can probably be resolved by modeling the different regime segments individually. Obviously this is a very difficult task to carry out for a number of markets, and with little forecasting value, as we know neither the timing of the next shock nor its effect on the returns generating mechanism.

[10] Granger and Terasvirta (1999), Granger and Hyung (1999) and Diebold and Inoue (2001) suggest some cases where structural breaks are closely related with long memory.In particular, Granger and Hyung find evidence of a time-varying long memory parameter in absolute S&P500 returns and suggest that a linear model with occasional breaks is appropriate for stock returns. In the context of emerging markets, Aggarwal et al (1999) identify sudden shocks/changes in the variance of returns of some emerging markets, mostly associated with local events, which thing suggests that ECM are segmented and thus little affected by world events.

2.2 The ARFIMA-FIGARCH Model

The discussion in the previous section leads us to conjecture that a good place to start for decribing the dynamic return generating process in ECM is the double long memory ARFIMA-FIGARCH model. We parametrize the conditional mean as an ARFIMA(5,d,0) process and the conditional variance as a FIGARCH(1,δ,1) process, according to the following specification:

$$\begin{aligned} \rho(L)(1 - L)^d(y_t - \mu) &= u_t \\ u_t = z_t\sigma_t,\ \ z_t &\backsim i.i.d.\, D(0,1) \\ \sigma_t^2 = \omega + \beta\sigma_{t-1}^2 &+ \left[1 - \beta L - (1-\varphi L)(1-L)^\delta\right] u_t^2 \end{aligned} \tag{1}$$

d and δ are fractional difference operators, L is the lag operator, $\rho(L) = 1 - \sum_{j=1}^{5} \rho_j L^j$, μ is the unconditional mean of the process y_t, u_t is white noise, and $\varphi = [1 - \alpha - \beta]$; all the roots of $\rho(L)$ lie ouside the unit circle. The lag order structure for the autoregressive component of the mean equation was chosen so as not to over-parametrize the model, while adequately describing the short-run dynamics. The same specification of the ARFIMA-FIGARCH model was also employed in Baillie et al (2002) to describe the dynamics of the daily DM/$ forward premium.

It is clear that under homoscedasticity the process reduces to an ARFIMA (5,d,0) model. Granger and Joyeux (1980) and Hosking (1981) showed that the autocorrelation coefficients of an ARFIMA model exhibit a slow hyperbolic rate of decay, which is characteristic of long memory processes.[11] For any process $y_t \backsim I(d)$, y_t will be stationary and invertible for $-0.5 < d < 0.5$ and will be mean reverting for $d < 1$; however, the presence of the long memory FIGARCH process implies an undefined unconditional variance for all d. It is evident from expression (1) that the ARFIMA (p,d,q) model reduces to a stable ARMA(p,q) process for $d = 0$ and to the nonstationary ARIMA(p,1,q) process for $d = 1$.

The conditional volatility dynamics follow a FIGARCH(1,δ,1) specification (Baillie et al (1996a)) which imposes an ARFIMA structure on u_t^2.[12] As for the ARFIMA class of models for the conditional mean, parameter δ captures the long memory effect and provides important information regarding the speed with

[11] The long memory property may also be defined in terms of the spectral density (see Beran (1994)). An alternative definition long memory is in terms of Wold decomposition. For a survey, see Baillie (1996).

[12] Independent research by Ding and Granger (1996) leads to a closely related model for the conditional valatility. Bollerslev and Mikkelsen (1996) extended the FIGARCH specification to a log transformation of the conditional variance process and proposed the Fractionally Integrated Exponential GARCH (see Nelson (1991)). This model, however, implies long memory features for the logarithm of squared returns, and since the discussion in the literature is mostly in terms of the levels of squared returns, we choose to work with the FIGARCH model which admits a more natural interpretation in terms of squared returns. In addition, the long memory stochastic volatility model was introduced by Breidt, Crato, and de Lima (1998). The much easier inferential procedures for ARCH-type models is one obvious advantage of the FIGARCH approach over stochastic volatility models.

which shocks to the volatility process are propagated, while φ and β describe the short-run effects. The FIGARCH(1,δ,1) model nests the stable GARCH(1,1) and IGARCH(1,1) specifications; when $\delta = 0$, the FIGARCH model in (1) reduces to a GARCH model and when $\delta = 1$, it reduces to an Integrated GARCH, or IGARCH(1,1) model. The FIGARCH process has impulse response weights of $\sigma_t^2 = \omega/(1-\beta) + \lambda(L)u_t^2$
where, $\lambda_k \approx k^{\delta-1}$, which is essentially the long memory property, or "Hurst effect" of hyperbolic decay. The attraction of the FIGARCH process is that for $0 \prec \delta \prec 1$, it is sufficiently flexible to allow for intermediate ranges of persistence (Baillie et al (1996)), in contrast with the GARCH class (Bollerslev (1986)) and IGARCH (Engle and Bollerslev (1986)) models.[13] Model (1) can be estimated, under the assumption of normally distributed innovations, by using non-linear optimization procedures to maximize the Maximum Likelihood function below:

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

where $\theta^{'} \equiv (\omega, d, \beta 1 ... \beta_p, \varphi_1 ... \varphi_q)$. Since most returns series are not well described by the conditional normal density in (5), the Quasi Maximum Likelihood Estimation (QMLE) technique of Bollerslev and Wooldridge (1992) is invoked to allow for asymptotically valid inference, where

$$T^{\frac{1}{2}}(\hat{\theta}_T - \hat{\theta}_0) \longrightarrow N\left\{0, A(\theta_0)^{-1}B(\theta_0)A(\theta_0)^{-1}\right\} \qquad (3)$$

and $A(.)$ and $B(.)$ represent the Hessian and outer product gradient respectively, both evaluated at the true parameters θ_0; $\hat{\theta}_T$ represents the estimates based on T observations.The consistency and asumptotic normality of the QMLE has only been established for specific special cases of the ARFIMA and/or FIGARCH model. In the context the FIGARCH(p,δ,q) model, detailed simulation evidence in Baillie et al (1996a) reveals that for the sample sizes typically encountered with financial data, this approximate MLE works extremely well in terms of estimating both the parameters of the process and their asymptotic standard errors. A fully general theoretical treatment however is as yet unavailable.[14]

Estimation of ARFIMA processes with time-varying heteroscedasticity is fairly new in the literature; Baillie et al (1996b) estimate an ARFIMA-GARCH process for the post-war inflation rates of several industrial countries. There are also some previous suggestions of using parametric double long memory

[13] Bollerslev (1988) showed that the squared residuals autocorrelation function in a GARCH(1,1) decreases exponentially. Ding and Granger (1996) extended these results for the general GARCH(p,q) case. Though not weakly stationary, IGARCH models are strictly stationary and ergodic (Nelson (1990), Bougerol and Picard (1992). Thus, although from a forecasting perspective shocks to the (future expected) conditional variance of the IGARCH model persist indefinitely, the effect of a shock on the "true" (i.e. actual, not forecasted) conditional variance process is not permanent; in fact, as shown by Ding and Granger (1996), the autocorrelation function for u_t^2 is exponentially decreasing, like standard stable GARCH models!

[14] Asymptotic normality and $T^{1/2}$ consistency of the QMLE estimator has been shown for the IGARCH(1,1) model by Lee and Hansen (1994) and Lumsdaine (1996).

models in the literature. Teyssiere (1998), Baillie et al (2002) and Beine et al (2002) apply such a model to high frequency exchange rate returns.Baillie, Han and Kwon (2001) showed the ARFIMA-FIGARCH model to be useful in describing monthly CPI inflation rates across countries. They also present simulation evidence to show that QMLE works quite well for estimating double long memory models, including the case of when the long memory in the mean parameter is between 0.5 and 1.

3 Data and Methodology

3.1 Data

The data set consists of Morgan Stanley Capital International (MSCI) daily stock index prices from 01/01/1988 to 14/05/2002, a total of 3761 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). The market indices are consistently computed across different emerging economies and, therefore, directly comparable. All indices are weighted by market capitalization (value-weighted). They are constructed so as not to double count those stocks multiple-listed on foreign stock exchanges. Stocks are selected for inclusion on the basis of liquidity and market value. We take 1988 as our starting date not only due to data availability, but also because prior to (around) this time the equity markets in our sample were almost inaccessible for direct investments by foreign investors. They were accesible primarily through country funds. Following previous studies on emerging markets (Bekaert (1995), Bekaert and Harvey (1995, 1997), Harvey (1995a,b), Garcia and Ghysels (1998), Barkoulas et al (2000), Wright (1999), Elekdag (2001)), we focus on dollar denominated series since this is presumably 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. To the best of our knowledge, the MSCI data set of emerging markets has not been used in previous research at the daily frequency. Most previous studies employ IFC monthly data dating back to 1975; we trade off the longer span for lower frequency samples in order to have a sufficient number of observations for our trading rules tests and statistical inferences.

3.2 Econometric testing

Starting with the ARFIMA(5,d,0)-FIGARCH(1,d,1) process in (1), [15] we arrive at the most parsimonious representation for the returns process in each market using the general-to-specific methodology. Estimation of the models is done by

[15] We recognize that the span of the data is important for long-memory inference. For this reason, and before making a final inference 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.

QMLE. Following the standard procedure in the literature, the truncation order of the infinite polynomials $(1-L)^d$ and $(1-L)^\delta$ is set to 1000 lags while initial conditions have been set to $u_{t^*}=0$ and $u_{t^*}^2=E(u_t^2)$ for $t^*=0,-1,-2,...,-1000$ and $t=1,2,....T$, where T is the number of observations.

A critical part of our econometric analysis is devoted to diagnostic tests in order to assess the relevance of our modeling amework, and in particular, to choose between competing nested models.The first test is the Ljung-Box (Q) statistic on standardized and squared standardized residuals to test the null hypothesis of no autocorrelation up to order 100.[16] The Q test on squared standardized residuals is an alternative to the Lagrange multiplier test proposed by Engle (1982) to evaluate the specification of a GARCH process. Bollerslev and Mikkelsen (1994) show that the Q test has considerable more power in detecting model misspecifications. It should also be noted that the Q test statistic assumes that the variance of the process is constant (homoskedasticity) so that critical values are merely indicative. Diebold (1988), among others, noted that the presence of ARCH may give rise to spurious significance of the portmanteau test. Nevertheless, Bollerslev and Mikkelsen (1996) showed that the Q test is still valid in detecting serial correlation. In addition we 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 (the BDS test can be viewed as a nonlinear analog of the Ljung-Box statistic). The BDS test attempts to distinguish between an i.i.d. series (null hypothesis) and a series with deterministic or stochastic dependence. It is calculated as

$$B_{m,T}(\varepsilon)=\frac{T^{1/2}\left[C_{m,T}(\varepsilon)-C_{1,T}(\varepsilon)^n\right]}{\sigma_{m,T}(\varepsilon)} \tag{4}$$

where $C_{m,T}(\varepsilon)$ is the sample correlation integral of embedding dimension m at distance ε, and $\sigma_{m,T}(\varepsilon)$ is an estimate of the asymptotic standard error of the numerator in equation (8). Under the i.i.d. null hypothesis, Brock et al (1996) prove that $B_{m,T}(\varepsilon)\backsim N(0,1)$. Following Baillie et al (2000) the embedding dimension in our tests was chosen to be in the range 2 through 10, while ε was fixed in the range of 0.25s through 1.25s, where s is the standard deviation of the data.[17] We also provide the Akaike (AIC) and Schwarz (SBC) criteria to compare the different model specifications. Monte Carlo simulations show that these criteria may be effectively used in discriminating between GARCH and

[16]The standard portmanteau test statistic $Q_m=T\sum_{j=1,m}r_j^2$, where r_j is the j-th order sample autocorrelation from the standardized residuals and T is the number of observations, is known to have an asymptotic chi squared distribution with $m-k$ degrees of freedom, where k is the number of parameters estimated in the conditional mean. Similar degrees of freedom adjustment are used for the portmanteau test statistic based on the squared standardized residuals when testing for omitted ARCH effects. This adjustment is in the spirit of Diebold (1988).

[17]Hsieh and LeBaron (1988) recommended choosing ε between 0.5 and 1.5 standard deviations of the data. The choice of m depends upon which lag the investigator wishes to test for dependence (Brock et al (1996)).

FIGARCH alternatives (Bollerslev and Mikkelsen, (1996)).[18] Finally, a robust Wald test is used to compare nested models, in particular, a stationary GARCH (1, 1) specification for the conditional volatility process versus a FIGARCH (1, d 1) model.

3.3 Technical Trading rules

Early empirical studies employed different trading rules to investigate the weak form of the efficient market hypothesis: filter rules (Fama and Blume (1966)), relative strength rules (Levy (1967a,b), Jensen and Benington (1970), Bohan (1981), Brush and Boles (1983), Jacobs and Levy (1988)), and moving average rules (Van Horne and Parker (1967), James (1968)), were all examined. By and large, the evidence from these studies generally indicated that trading strategies based on exploiting apparent trends in historic share price data did not yield returns that were superior to a buy-and-hold strategy, even before taking transaction costs into account. More recent evidence (Sweeney (1988), Corrado and Lee (1992), Chelley-Steeley and Steeley (1997) on filter rules, Levich and Thomas (1993) on both filter and moving average rules, Osler and Chang (1995) on head and shoulder patterns) suggests that technical trading rules may have some predictive ability. Novel evidence in favor of technical analysis is provided by Brock et al (1992) and Hudson et al (1996), who employ simple moving average and trading range break rules in the US and UK respectively; the former study analyses daily data on the Dow Jones Industrial Average (DJIA) for a 90-year period from 1897 to 1986, while Hudson et al examine Financial Times Industrial Ordinary Index (FTI) prices over a 59.5-year period from 1935 to 1994. The Brock et al. results are augmented and supported by Sullivan et al (1999) who employ a neural-network technique to examine, what they claim to be, the near-univerese of technical trading rules applied to the DJIA. The message from these investigations is that the predictive ability of trading rules is uncovered if sufficiently long data series are considered. This may be the reason behind the strong support for technical analysis, unlike earlier studies. In both the US and the UK, buy signals offer positive returns whereas sell signals offer negative returns; the sell signals seem to have greater predictive ability (in statistical terms) than their buy signal counterparts. For example, Brock et al. find that the average 10-day return based on the trading range breakout rule stands at 0.63% for buy strategies and -0.24% for sell strategies. Similar results emerge in the UK investigation by Hudson et al. - the average 10-day holding

[18] The AIC and SBC to be minimized are defined as follows:

$$AIC = -2Loglik() + 2\gamma$$

$$SBC = -2Loglik() + \gamma \log T$$

where γ denotes the number of estimated parameters, $Loglik()$ is the value of the Log-likelihood and T is the number of observations used for the estimates. It should be noted that the use of such information criteria in ARFIMA-FIGARCH models remains to be investigated. Such an investigation, while interesting in its own right, is beyond the scope of this paper.

period return on buy strategies based on the trading range breakout rules is 0.70%, while the average return for sell strategies is -0.43% - . In particular, Brock et al. find that trading rule returns significantly outperfrom a benchmark of holding cash, though they don't closely examine whether their trading rules can be used to earn excess returns in a costly trading environment. Hudson et al. integrate transaction costs to their analysis to find that the technical rules are unlikely to yield returns over and above the buy-and-hold strategy in the UK.

Like the Brock et al (1992) and Hudson et al (1996) studies, the present study implements two of the simplest and most widely used technical trading rules to MSCI stock price indices of eight ECM: the moving average-oscillator and the trading range breakout (resistance and support levels). We are interested in the potential profitability of such rules over some benchmark (the buy-and-hold strategy), as well as the informational content they carry about predictable (probably "hidden") patterns in the returns time series, and implications regarding the source of excess returns. Trading rule results can also be used as a specification test for the proposed underlying econometric model.

We only use simple rules that have been utilized for over sixty years by practitioners and appear in previous research. In doing so we make sure that outperforming trading rules have consequences for weak-form market efficiency or variations in ex ante risk premia, since these rules were well known over the sample and could be implemented (Sullivan et al, 1999). Stock prices are probably the most studied financial series and, therefore, most susceptible to data-snooping. Undoubtedly some rules will work if one searches hard enough. In order to minimize data-snooping biases we employ a new data set on emerging market indices that has not been studied much in the past. Moreover, we do not search over different trading rules but just apply eight cross-over moving-average rules and six trading-range break ones that appear in Brock et al (1992), and report the results from all the rules. Our rules also check for the sensitivity of the results to the exact moving-average lengths used by examining different, popular, lengths.

The variable length moving average filter used in this study places emphasis on whether the short-run moving average is above (below) the long-run moving average suggesting that the more recent price is above (below) the longer term price level and that the general trend in prices is upward (downward). Proponents of these rules do not only argue that analysis of moving averages helps identify trends in the series, but also that computation of moving averages smooths out an otherwise volatile series. As in Brock et al (1992) we test some of the most popular rules; 1-50, 1-150, 1-200, 5-150,[19] with and without a band of 1% which reduces the number of buy (sell) signals by eliminating "whiplash" signals when the short and long period moving averages are pretty close. This

[19] The first number refers to the length of the short (therefore fast) moving average and the second number to the length of the long (therefore slow) moving average, eg. in the 1-50 rule the short period is one day and the long-period is 200 days. The moving average for a particular day is calculated as the arithmetic average of prices ove the previous n days, including the current day.

method simulates returns from a strategy where traders go long as the short moving average moves above the long by an amount bigger than the band, and stays in the market until the short moving average penetrates the long moving average from above by an amount bigger than the band. After this signal the investors either liquidate their positions or sell short. If the short moving average is inside the band no signal is generated. With a band of zero all days are classified into buys and sells.

For the trading range break-out rule (TRB) a buy signal is generated when the price penetrates the resistance level, defined as the local maximum price over some previous days. A sell signal is generated when the price penetrates the support level, defined as the local minimum price over the predefined days. If the price drops below the support level, it is assumed that the price will continue to fall and, therefore, it is advisable to sell. For practical purposes, and also for the purposes of consistency with the other technical rules and previous studies, maximum and minimum values were calculated for the 50, 150 and 200 previous days. Again we do not experiment with the holding period to avoid data-snooping. In addition, each rule is implemented with a 1% band, whereby the price level must exceed the local maximum by 1% or fall below the minimum by 1%. As in Brock et al (1992), for this rule we compute 10-day holding period returns following buy and sell signals, ignoring other signals occuring during this 10-day period.

The statistical significance of the trading rule returns are evaluated using t-statistics. For the buy and sell returns, the t-statistic for the null hypothesis that the mean buy and sell returns are not statistically different from the unconditional returns in each market is:

$$\frac{\mu_r - \mu}{(\sigma^2/N + \sigma^2/N_r)^{1/2}} \tag{9a}$$

where μ_r and N_r are the mean return and number of signals for the buy and sells, μ is the unconditional mean , N is the number of observations and σ^2 is the estimated unconditional variance for the entire sample. For the buy-sell difference the t-statistic for the null hypothesis of equality with zero is

$$\frac{\mu_b - \mu_s}{(\sigma^2/N_b + \sigma^2/N_s)^{1/2}} \tag{9b}$$

where μ_b and μ_s are the mean returns for the buys and sells respectively, and N_b and N_s are the number of signals for the buys and sells.

3.4 The Bootstrap Methodology

The purpose of using bootstrap techniques with our trading rules tests is to fill in some gaps left by technical analysis and standard statistical procedures. First, to compute a comprehensive test across our set of trading rules is a very difficult task, given that individual rules only differ either by the length of the moving average and/or a 1% band. This implies that there are complex dependencies between trading rule results that are difficult to account for by standard statistical techniques.[20] The major advantage of utilizing bootstrap distributions for the trading rule statistics is that a joint test of significance for our set of trading rules can be developed; a joint test statistic can be constructed as a result of any function that aggregates results across the various rules. We choose to take simple averages as this function has been used in the past (in Brock et al (1992)) for reasons of comparability. In addition, the bootstrap distributions from the simulated null models can address important aspects of the data (as revealed in Tables) such as skewness, leptokurtosis, autocorrelation and conditional heteroscedasticity; this is in contrast with t-ratios which assume normal, stationary, and time-independent distributions and can thus lead to questionable conclusions regarding the significance of trading results. A third benefit of this methodogy is that we can examine the standard deviations of returns during buy and sell periods, which provides an indication for the riskiness of the trading strategies within the sample period relative to the buy-and-hold benchmark.

The application of the bootstrap methdology in combination with technical analysis is not particularly new to the finance literature. Most notably, Brock et al (1992) augment the standard tests of significance of trading rule results with the bootstap methodology inspired by Efron (1979), Freedman and Peters (1984a, 1984b), and Efron and Tibshirani (1986), for more powerful statistical inferences.Moreover, they test the adequacy of four popular null models for the generation of stock market prices using boostap simulation techniques, and apply the trading rules on the simulated series to evaluate the different model specifications. They find that trading rule profits on the DJIA are not consistent with a random walk model, an autoregressive model of order 1 (AR(1)), a GARCH-in-mean model (GARCH-M), or an exponential GARCH (EGARCH) model. Levich and Thomas (1993) use bootstrap simulations to assess the significance of trading rule profits on their exchange rate series by comparison to the empirical distribution of results derived from the randomly generated series (their resampling technique implicitly assumes that exchange rate returns follow a random walk). We follow a slightly different approach in that using econometric techniques we first choose an appropriate model from the ARFIMA-FIGARCH framework for the returns generating process in the eight emerging markets. By modeling both conditional mean and conditional volatility dynamics in econometrically supported parsimonious specifications, we have a more complete framework for the evaluation of trading rule results than has been used in previous research.We simulate the preferred model and evaluate the significance of the trading rule results relative to the simulated null model. At the same time the trading models act as a specification test for the simulated underlying process.

[20]It is sometimes possible to determine the dstributions of statistics based on sums of correlated random variables. However, in this case the distribution of these random variables is unknown

3.4.1 The Bootstrap Test

The objective of a general (two-sided) test is to compute the p-value function

$$p(\hat{\tau}) = p(|\tau| \geq |\hat{\tau}| \ / \ \Psi_0, T) \tag{10a}$$

where Ψ_0 is the data generating process (DGP) under the null hypothesis, and $\hat{\tau}$ is the realized value of a test statistic τ based on a sample of length T. Since Ψ_0 is unknown, this p-value function has to be approximated , which is regularly done using asymptotic theory. For asymptotic theory to be valid it is required that $p(\hat{\tau})$ should not depend on Ψ_0 and T, which is usually not true in small samples. An alternative to an asymptotic solution is to estimate the finite-sample DGP by the bootstrap DGP, $\widehat{\Psi}_0$, that is, to use a bootstrap test. According to Davidson and Mackinnon (1996) a bootstrap test is understood as a test for which the significance level is calculated using a bootstrap procedure. They argue that the size distortion of a bootstrap test is of the order $T^{-1/2}$ smaller than the correspomding asymptotic test.

If R bootstrap samples, each of size T, are generated in accordance with $\widehat{\Psi}_0$ and their respective test statistics τ_r^* are calculated using the same test statistic τ as above, the estimated bootstrap p-value function is defined by the quantity

$$p^*(\hat{\tau}) = R^{-1} \sum_{r=1}^{R} I\left(|\tau| \geq |\hat{\tau}|\right) \tag{10b}$$

where I is equal to 1 if the inequality is satisfied, and 0 otherwise. The null hypothesis is rejected when the selected significance level exceeds $p^*(\hat{\tau})$. In our case, the DGP under the null hypothesis for the emerging market stock returns are as inferred from the econometric results. The statistics of interest are the buy returns, sell returns, buy-sell difference, and standard deviations of buy and sell returns.The simulated p-value for each statistic is the fraction of the simulated series which produce a value for the statistic bigger than that of the actual series.

3.4.2 Construction of the Bootstrap samples

Almost immediately following Efron's (1979) paper on bootstrapping i.i.d data, the residual-based (or model-based) bootstrap for linear regression and autoregression was introduced and studied (see, for example, Freedman (1981, 1984), Freedman and Peters (1984a,b), Efron and Tibshirani (1986, 1993)). Our approach is based on these papers, as well as Andersson and Gredenhoff (1998) who bootstrap autoregressive but heteroscedastic models . The use of a model-based bootstrap maintains dependencies in the data and is able to generate new bootstrap stationary pseudoseries;[21] it is a natural way to proceed in our case

[21] A model free procedure, such as a moving blocks bootstrap, may also preserve dependencies. However, model free approaches deviate from the bootstrap testing idea of Davidson and Mackinnon (1996a, b), in the sense that resemblance between the bootstrap samples and the original sample is sacrificed.

since well-defined stationary models to describe the DGPs of emerging market stock returns form the null-hypothesis (AR-FIGARCH models, as shown in section 5.2).[22]

In our procedure, the standardized residuals (residuals divided by their standard deviation) from the chosen model ($\hat{u}_t$) are redrawn with replacement from the recentered and degrees of freedom corrected residual vector to form a scrambled (standardized) residual series,

$$\overline{u}_t = \sqrt{\frac{T}{T-K-1}}\hat{u}_t \tag{11}$$

where k is the number of estimated parameters in the mean equation and $\hat{u}_t$ is $U(k+1, T)$ distributed. This non-parametric resampling scheme does not impose distributional assumptions and allows the scrambled standardized residuals to deviate from Gaussianity. The bootstrap residuals are then built by imposing the *estimated* conditional dependency according to the preferred specification - a FIGARCH(1, δ, 1), or FIGARCH (1, δ, 0) in which case the $(1-\widehat{\varphi}L)$ factor in the expression below disappears -,

$$\overline{\sigma}_t^2 = \widehat{\omega} + \widehat{\beta}\overline{\sigma}_{t-1}^2 + \left[1 - \widehat{\beta}L - (1-\widehat{\varphi}L)(1-L)^{\widehat{\delta}}\right] u_t^{*2} \tag{12a}$$

and

$$u_t^* = \overline{u}_t\sqrt{\overline{\sigma}_t^2} \tag{12b}$$

Finally, the bootstrap samples y_r^*, $r = 1, ..., R$, are created recursively by the equation

$$(y_{r,t}^* - \widehat{\mu}) = \widehat{\rho}(L)^{-1}u_t^* \tag{13}$$

where $\widehat{\rho}(L)$ is the *estimated* polynomial of equation (7), which differs of course for each market, and u_t^* are the bootstrap residuals. In this study the number of bootstrap replicates is $R = 1000$,[23] each with 3760 observations as the original returns series. The returns series are then exponentiated back into a price series.[24] To account for possible initial-value effects (we use actual returns values and the initial error terms from the estimated models as starting values

[22] The long momory volatility parameters for each market lie in the stationary region, $0 \leq \delta \leq 1$, and thus our AR-FIGARCH models are stationary (have stable Paretian distributions).

[23] Using 1000 repetitions of estimates of objects such as $p(\tau \geq \hat{\tau})$, where τ is a random variable and $\hat{\tau}$ is a constant, will have a maximum standard error of $\sqrt{(0.5^2/1000)} = 0.016$. This is an upper bound on the precision of our estimates and probably exceeds our actual standard errors. As by using the estimation-based bootstrap in the context of AR-FIGARCH models we are taking the procedure beyond what has been proved in the bootstrap literature, we test the reliability of our estimates by extending the number of replications to 2000. We do this for the most profitable moving average and TRB rule in each country (and this is important because of different estimates for δ). We find that extending the number of replications beyond 1000 adds very little to the reliability of estimated p-values (results available upon request).

[24] For a rigorous theoretical treatment of the bootstrap procedure for stationary and ergodic processes see, among others, Brock et al (1992). More details on the practical implementation are available upon request.

to begin the recursions), and for the fact that the FIGARCH process requires a large number of observations to have a full impact (because of the δ term), we repeat the above procedure generating 100, 500, and 1000 additional observations, which are then removed. We find there is very little difference among the simulated series and thus present results with 100 additional observations generated (and cut out).

We then follow Brock et al (1992) in combining tests based on technical trading rules with bootstrap techniques for generating distributions for the buy, sell, buy-sell, and standard deviations of buy and sell statistics under the simulated null models.

4 Empirical Results

4.1 Summary Statistics

Tables Ia and Ib contain summary statistics for the continuously compounded daily stock index returns of the Asian and Latin American markets respectively. The buy-and-hold strategy (unconditional) returns over the whole sample period seem to be 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). Interestingly enough, the Asian markets exhibit positive skeweness, 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 footnote 2); Bekaert et al (1998) note that when integration brings about stock market development that leads to more companies seeking a stock market listing and eventually a more diversified index, skewness (and kurtosis) may decrease. Stock index returns from all markets are leptokurtic, in the sense that the kurtosis for all these returns is bigger than that of a normal distribution, which is 3 (tables Ia and Ib show excess kurtosis). The Jarque-Bera normality indicates that all the eight return series are not normal (p-values in brackets). These findings are in agreement with other emerging market studies (e.g. Bekaert and Harvey (1997), De Santis and Imrohoroğlus (1997), Choudry (1996)), and point to similarities in distribution of returns for both developed and developing markets. In turn, the Augmented Dickey-Fuller (Dickey and Fuller (1981)) test suggests that the null hypothesis that returns are nonstationary (i.e. have a unit root and are thus I(1) processes) can be rejected, indicating that the stock index price series can be treated as integrated of order one (I(1)) processes (and returns as I(0)).

In addition, the numerical values for the sample autocorrelations for returns and squared returns for the eight markets at lags 1, 2, 3, 4, 5, 10, 100 are presented. The Barlett standard error is calculated as two times the standard error of the sample autocorrelations for the corresponding series if they are not correlated and have finite variances, and as such can only be used as an approximate guide to the significance of autocorrelation statistics. It is seen that for the returns series only one (for Philippines), or two (for Mexico, Brazil), or three (for Argentina, Taiwan, Thailand) or at most four (for Chile, Indonesia) lags of sample autocorrelations of those shown are significantly different from zero. 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 (similar observations made by Ding and Granger (1996) for a number of speculative asset returns). 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.[25]

4.2 Econometric Results

In Tables IIa-h we present the results of estimating parsimonious specifications of model (2). First, in all markets, we fail to reject at conventional significance levels the null of no fractional integration in the mean, once we allow for short-term dependencies. Therefore, we re-estimate the models constraining d to be zero. This is in contrast with the studies by Wright (1999 and 2001) and Barkoulas et al (2000), which using monthly IFC and weekly data (for Greece) respectively report some evidence in favor of long memory in emerging market stock returns.[26] Note that lag order selection issues are important when building a dynamic model. To determine the appropriate autoregressive (AR) order in each market, we rely on the standard errors for the estimated coefficients and the AIC-SBC criteria. In a first step, we select the AR terms, assuming a FIGARCH (1,δ,1) specification. Then, given the obtained AR specification, we compute the information criteria in order to choose the FIGARCH orders and compare with GARCH (1,1) and IGARCH (1,1) specifications for the conditional volatility. As shown in Tables IIa-d, an AR(1) specification in the conditional mean has been retained, among the Asian countries, only for Philippines, while Indonesia and Thailand support an AR(2) specification, and Taiwan follows an AR(3) process. Among Latin American countries, Mexico and Brazil are found to be AR(1) in the conditional mean, while results for

[25] 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.

[26] Both Wright (1999) and Barkoulas et al (2000) use the Geweke and Porter-Hudak estimator (1983) which is not robust to short-run dynamics. Moreover, through extensive Monte Carlo simulations Cheung (1993) and Agiakloglou et al (1993) found the spectral regression test to be biased towards finding long memory in the presence of infrequent shifts in the mean of the process and large AR parameters (>0.7). We disregard semi-parametric estimation procedures in general as "Despite the amount of theoretical work in attempting to derive robust semiparametric estimators of long memory parameters, there is substantial evidence documenting their poor performance in terms of bias and mean squared error." Baillie (1996, p.35). In addition, semi-parametric tests do not allow joint estimation of short- and long-memory components. Finally, although Wright (2001) employs the ARFIMA model to find some evidence in favor of long memory, he does not model conditional volatility dynamics at all, thus not accounting for the impact of heteroscedasticity on the standard errors of his coefficient estimates.

Chile support an AR(2) specification and for Argentina AR(3). De Santis and Imrohoroğlus (1997) introduce a lagged return variable in the conditional return model to capture serial correlation potentially induced by non-synchronous trading in the assets that make up the market index and/or thin trading. These problems can be particularly severe in emerging markets, given their low level of liquidity. The (more than one in most markets) significant autoregressive coefficients may enforce the claim of persistent emerging market returns, in contrast with results for the United States and other developed markets where there is little evidence for any serial correlation in stock returns. Our results are not at odds with Bekaert (1995) either, who suggested that in emerging markets, it is often possible to predict future returns, using only lagged returns. Note also that excluding the AR(2) parameters in Chile and Argentina (in the case of Chile the AR(2) parameter is only equal to -0.052 whereas the positive AR(1) parameter equals 0.276), all the other estimated AR parameters are positive, which apart from another indication of persistence, this is also not supportive of the mean reversion hypothesis in emerging markets (in agreement with findings by Titman and Wei (1999), De Santis and Imrohoroğlus (1997)). Finally, the positive serial correlation in emerging market stock returns, which could be the result of an autoregressive process that generates stock returns, might be responsible for the "abnormal" trading strategy returns and positive buy-sell differences, as seen in later sections.

As far as conditional volatility dynamics are concerned, the GARCH parametrization is statistically significant in all cases. In all markets, the β coefficient in the GARCH(1,1) equation is considerably larger than α, implying that large market surprises induce relatively small revisions in future volatility.[27] The persistence of the conditional variance process as measured by β and $\alpha + \beta$ is high (sum close or bigger than 1), particularly for all Asian markets, as well as Brazil and Argentina from the Latin American markets, suggestive of IGARCH type of behavior. For Brazil, Argentina and Thailand, the IGARCH(1,1) is preferred according to AIC/SBC criteria to the GARCH(1,1) specification (while retaining ofcourse the same specification for the conditional mean).

Focusing now on the FIGARCH and overall model results, the fractional differencing parameter in the volatility (δ) is estimated in all markets as significantly different from zero, implying fractional integration. Note that δ is always in the stationary region (between 0 and 1). For all countries, the estimate of β falls considerably as one moves from GARCH to FIGARCH, in line with the findings of Baillie et al (1996a). They claim that, in the presence of long memory, there is an upward bias in the GARCH estimates due to the fact that the GARCH model does not take into account the long memory component of the volatility process. Most importantly, a robust Wald test of a stationary GARCH(1,1) model under the null hypothesis versus a FIGARCH(1,δ,1) under the alternative hypothesis has numerical values ranging from 51.89 in Philippines to 429.93 in Indonesia, providing overwhelming rejections of the

[27] Results are consistent with Fraser and Power (1997), Choudry (1996) and De Santis and Imrohoroğlus (1997). The latter use a GARCH model to find predictability, clustering, and persistence in the conditional volatility of many emerging market stock returns.

GARCH(1,1) formulation in all markets. Moreover, according to the AIC and SBC criteria, the AR-FIGARCH models fit the returns series better than the AR-GARCH models. Also, the movement from GARCH (and IGARCH) to FIGARCH volatility specification is associated with a drop in Q statistics for squared standardized residuals in almost all markets. Particularly in Thailand and Chile, the $Q^2(100)$ statistics show that there is still some significant serial correlation left in squared standardized residuals if conditional volatility is modeled as a GARCH(1,1) or IGARCH(1,1) process; the $Q^2(100)$ statistics fail to reject the null of no autocorrelation in squared standardized residuals once volatility is modeled as a FIGARCH process. In general, the Q(100) and $Q^2(100)$ statistics for standardized and squared standardized residuals respectively fail to reject the null hypothesis of no autocorrelation for the preferred model specification. The preferred models for the Asian markets are: 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. It should be noted that the conditions for the conditional variance to be positive are always satisfied for the chosen models.[28]

Finally, the BDS test statistic on the standardized residuals from the preferred models does not produce significant evidence against the null hypothesis of identically and independently distributed residuals.[29] This, in conjuction with the Q-statistics, suggests that standardized residuals are i.i.d.

4.3 Trading Rule Results

Results from trading strategies based on moving average and trading range break rules are presented in Panel A of Tables IIIa-IIIh and Tables IVa-IVh respectively. The first collumn in Panel A of each table contains descriptions of the rules used. For example, in the case of the (1,50,0.01) moving average rule, the first number indicates the length of the short moving average (one day), the second number the length of the long moving average (50 days), and the band is 0.01 percent. The (1,50,0.01) trading-range break rule refers to local extrema calculated over the 50 preceding days with a band of 0.01 percent included to generate signals. The number of buy and sell signals is reported separately in the next two collumns, followed by the average buy and sell returns. The numbers in parenthesis below the returns are standard t-statistics (see expressions 9a and 9b) to evaluate whether the mean buy and sell returns are statistically different from the unconditional one-day (10-day in the case of TRB rules) return in each market. Next, the fractions of positive buy and sell signals appear for each

[28] Bollerslev and Mikkelsen (1996) derive sufficient conditions for the case of a FIGARCH (1,δ,1) process as $\beta - \delta \leq \varphi \leq \frac{1}{3}(2-\delta)$, and $\delta\left(\varphi - \frac{1}{2}(1-\delta)\right) \leq \beta\left(\varphi - \beta + \delta\right)$. Positiveness of the conditional variance was also checked on a case-by-case basis.

[29] As noted earlier, for purposes of robustness the test was conducted for embedding dimensions of 2 up to 10 and distances of 0.25s and 1.25s, where s is the stndard deviation of the data. Results are available upon request.

rule, and in the last collumn we have the difference between the mean buy and sell returns. The null hypothesis of the t-tests carried out for this difference is of equality with zero. Finally, the all-rules average daily (10-day for TRB) and average annualized buy, sell, and buy-sell returns are calculated for each market.

We first make some general comments which hold across all rules (both of the moving average and TRB type) and countries before discussing individual country results. Regarding characteristics of trading strategy results, returns following buy signals are positive, while sell returns appear to be negative. Moreover, the proportion of buy returns greater than zero is bigger than the corresponding proportion of sell returns almost for every rule and market. If technical trading rules do not produce useful signals, the fraction of positive returns should be the same for both buys and sells.The negative average returns following sell signals are especially noteworthy, as they cannot be explained by various seasonalities, being based on a large proportion of all trading days. This is evidence in favor of stock returns predictability, which is unlikely to reflect time-varying risk premia in the context of equilibrium models, but rather market inefficiencies. It is hard to imagine an equilibrium model that predicts negative returns over such a large fraction of trading days.[30]

4.3.1 Asian Markets

Tables IIIa-IIId and IVa-IVd report Asian country results for the moving average and TRB rules respectively (Panel A). Overall, there is no strong evidence in favor of either bullish or bearish markets over the period. The number of buy signals is only marginally higher than the number of sell signals in Philippines and Taiwan, with the first two rules in Taiwan actually producing a bigger number of sell signals. For most rules, sell signals in Indonesia and Thailand exceed buy signals, but not by much. This is in contrast with the results of Brock et al (1992) and Hudson et al (1996), which find clear evidence for upward-trending markets in the US and UK respectively, observing buy signals to be 50% higher, on average, than sell signals. The difference in our results may be attributable to the high sensitivity of these markets to local, regional, and global events (Gunasekarage and Power (2001)).

Starting with moving average rules, in the case of Philippines, there are significantly positive mean daily buy returns for two moving average rules at the 1% level, and two at the 10% level. The all-rules average daily buy return is equal to 0.1193 percent (31% at an annual rate), which is substantial relative to a "null" trading system which is always out of the market, and also compares favorably with the unconditional (buy-and-hold) one day return of 0.00560 (1.5% at an annual rate) from Table IIa. That is, the average buy return of the

[30] Similar results are obtained in the contect of the DJIA in the US (Brock et al (1992)). This is not too surprising since the data covers a period of 90 years, including time periods during which the US was an emerging market itself, and arguably inefficient. It would be interesting to apply and compare results with this methodology for the latter 15-20 year period (the Brock et al sample goes up to 1986).

moving average strategy exceeds the unconditional one-day return by a factor of about 20! The striking result is that mean sell returns are negative and highly significant for all rules, while all the buy-sell differences are positive and the t-tests for these differences are highly significant (all t-ratios bigger than 3), rejecting the null hypothesis of equality with zero. These results suggest the presence of long-run dependencies that drive the trading rule results . The average sell return for the eight rules is -0.1533 percent which is about -40% at an annual rate. Consequently the mean buy-sell difference rate of return reaches an annualized value of 71 percent - almost 50 times bigger than the buy-and-hold average return -.

Moving average rule results follow a very similar pattern in the other Asian countries. Average buy returns are positive for all rules but significant for the two shorter rules only, the (1,50,0) and (1,50,0.01). On the contrary, sell returns are negative and usually highly significant, excluding the (5,150,0) and (5,150,0.01) rule sell returns in Thailand which are negative but insignificant (see tables IIIa-IIId). In addition, average sell returns exceed average buy returns in absolute value in all Asian countries. The buy-sell difference is positive and highly significant across all rules; the average annualized buy-sell difference is 67% in Taiwan and Thailand, whereas in Indonesia it is much higher compared with the other three Asian countries (99%!). Across all rules and countries, the buy returns, (absolute) sell returns, and buy-sell differences are many times bigger than the unconditional one day return. These results clearly reject the null hypothesis that the returns to be earned from moving average rules are equal to those from a naive buy and hold strategy and thus offer degrees of predictive ability in Asian markets. This rejection holds for all four countries examined which suggests that any evidence of inefficiency is not specific to one size or age of market studied.

It should also be noted that the two shortest-length moving average rules, (1,50,0) and (1,50,0.01), exhibit much higher returns compared with the other strategies, with the (1,50,0.01) rule yielding the largest profit in all markets. In general, excluding the (1,200,0) and (1,200,0.01) rules in Indonesia which produce higher returns than the (1,150,0) and (1,150,0.01) rules respectively, a comparison of the different rule results in Panel A of tables IIIa-d indicates that as the length of the long moving average period increases, the buy-sell profit earned from the rule declines. For example, a comparison of the (1,50,0), (1,150,0), and (1,200,0) strategies in Panel A of TableIIb for Taiwan shows that profit falls from 0.003856 to 0.002414 to 0.002016. Also, as the length of the short moving average increases the buy-sell profit declines. For example, comparing the (1,150,0) with the (5,150,0) rule in Taiwan we can see that profit falls from 0.002414 to 0.001769. Finally, the introduction of the bandwidth investigated (0.01) increases profits, though this is not always the case. The analysis of the different strategies therefore indicates that while all beat the naive buy-and-hold portfolio the rigorous selection of long moving average, short moving average and bandwidth can increase profitability even further.

The TRB rule results do not follow as clear a pattern across Asian countries as the above results. What can be observed though is that compared with correspondng moving average rules for each country, results on the significance of buy and sell returns appear to be reversed; TRB rule buy returns are on average stronger, more significant, while results for sell returns are weaker. For example, in the case of Philippines, buy returns are positive and significant for all rules, while sell returns are significantly negative for four out of the six rules tested. Mixed results for the significance of buy and sell returns are obtained for Taiwan, while Thailand and Indonesia generally produce positive, statitistically significant buy returns, and negative, mostly insignificant sells. In addition, excluding Taiwan, average buy returns in the other Asian countries are bigger in absolute value than average sell returns. These results suggest that buy signals are at least as equally important as sell signals in predicting future trends in share returns. As with the moving average strategy, the buy-sell difference is positive and (mostly highly) significant for all trading strategies and countries but 3 TRB rules in the case of Thailand. Finally, the TRB rules produce quite substantial returns relative to a "null" strategy and the unconditional 10-day return as can be seen in Tables IVa-IVd; for example, the all-rules average annualized buy-sell difference ranges from 86% in Thailand to 186% in Indonesia! The evidence from this paper suggests that the TRB rules outperformed the moving average rules for this time period in each Asian market.

As with moving average rules, the Indonesian market is the most profitable one, followed by Philippines. The actual profits, however, that can be derived from these trading rules depend on the frequency of trades and the associated transaction costs, which can quite exceed those in developed markets. Let's explore the following strategy proposed by Brock et al (1992) (and also Sullivan et al (1999)): upon a buy signal, the investor borrows in order to double his investment in the index, a "neutral" signal translates into simply holding the index, while upon a sell signal the investor sells shares and invests in a risk-free asset. Given that the number of buy and sell signals in the TRB rules is similar, we assume that borrowing and lending rates are the same and that risk during buy periods is the same as risk during sell periods. Under these assumptions, such a strategy should produce the same return before transaction costs as the buy-and-hold. Taking the (1,150,0) TRB rule in Philippines as an example (buy-sell difference strongly significant), there are on average about 3.1 buy and sell signals per year. On the buy side the inestor gains on average 5.8 percent (3.1×0.018708) due to leverage. On the sell side, by not being in the declining market, he gains on average 7.8 percent (3.1×0.025192). That's a total of 13.6 percent, before transaction costs, which is about 9 times higher than the unconditional 1.5 percent average annual return on the MSCI Philippines index! Van der Hart et al (2003) use estimates of transaction costs faced by large institutional investors of between 1 and 2 percent in evaluating the profitability of various stock selection strategies in 32 emerging markets (see footnote 4). Even after using the upper limit of 2% we see that the above trading strategy yields average annual excess returns of 1.4%. In all Asian markets some TRB rules (of those which generate significant buy-sell differences) can produce excess returns. The (1,200,0) and (1,200,0.01) rules in Indonesia, which generate very high returns but not many signals, allow for an average annual excess return of about 8 percent on the assumption of 2 percent transaction costs, which compares with the 1.3 percent return of the benchmark strategy! Similar results are obtained for the TRB (1,150,0) and (1,150,0.01) rules with excess returns that beat the benchmark. The (1,200,0), (1,200,0.01) rules in Philippines, the (1,50,0) and (1,50,0.01) rules in Thailand, and the same rules in Indonesia, generate excess returns over and above the relevant benchamark in each country up to and including 2 percent transaction costs. On the contrary, in Taiwan none of the rule returns beat the benchmark after deducting 2 percent costs.

4.3.2 Latin American Markets

The Latin American market results are exhibited in Panel A of tables IIIe-IIIh and IVe-IVh. For all rules and markets, the number of buy signals exceed the number of sell signals with particularly clear evidence in favor of a primary upward trend in Mexico. Moving average rule results follow a very similar pattern in Mexico and Brazil (tables IIIe and IIIf). Positive, significantly different from the unconditional 10-day mean, buy returns are recorded for the two faster rules (1,50,0) and (1,50,0.01), as well as significant negative sell returns for the same rules. All other moving average strategies produce positive buy and negative sell returns, which are however insignificant. In both countries buy-sell differences are positive for all rules but significantly different from zero for the first four rules only. In the case of Argentina, all buy and sell returns are insignificant, while only the buy-sell differences of the two faster rules significantly differ from zero. These results suggest that there is less persistence in Latin American stock market returns compared with Asian markets. Trading rules cannot detect long-run depedencies in the data which would make long-length moving average rules statistically profitable, as in Asian markets. Chile is an exception, with a pattern of results resembling that from Asian markets. Significant buy returns are recorded for five out of the eight rules (though returns from two of these rules are significant only at the 10 percent level), while negative and significant sells are found for seven rules (two weakly significant); all buy-sell differences are positive and mostly highly significant. In all markets, if and where buy and sell statistics are significant, buy and sell signals are equally powerful for predictive purposes, consistent with inferences from Asian market results and in contrast with the US and UK studies which find sell signals to be more powerful.

As with Asian markets, in all Latin American countries we can generally observe that increasing the length of the long moving average results in a decrease in buy-sell profit; increasing the length of the short moving average, all else constant, also causes a decline in buy-sell profits. The introduction of the 1 percent band has mixed effects across countries. In all markets, the most profitable rule is the (1,50,0.01), cosistent with the Asian countries result.

Average buy, (absolute) sell, and buy-sell return differences are substantial relative to a zero return benchmark of always being out of the market, but are not as overwhelming relative to the 10-day mean return. This is not only because the buy-and-hold return is much higher in Latin America, but also because average trading rule returns are lower (particularly sells); the average annualized buy-sell difference ranges from 37 percent in Argentina to 58 percent in Brazil, while the lowest corresponding return in Asian markets is the 67 percent return in Thailand and Taiwan.

The pattern of results of TRB rules is more consistent across Latin American countries than Asian markets, and is comparable to the moving average rule characteristics. Trading rule returns are insignificant in Mexico, excluding the (1,50,0) TRB rule buy return and buy-sell difference. Buy returns in Brazil are positive but insignificant for all TRB rules, while sells are negative and significant (and buy-sell differences positive and significant) for only the first two faster rules. In Argentina TRB rule returns are insignificant, as are moving average returns. In Chile, consistent with moving average rules, we generally observe significant positive buy and significant negative sell returns, while buy-sell differences are positive and strongly significant for all rules. The significant predictive ability of both types of trading rules examined in this study for the Chilean market, contrary to the other Latin American countries but resembling Asian market results, may be attributed to the fact that Chile has been relatively more "close" over the sample period than the other Latin American markets (see footnote 2). According to the trading rule results, the less integrated Asian markets, togeher with Chile, seem to be "less" efficient than the other Latin American countries, offering opportunities for abnormal profits.[31]

Average TRB rule returns are stronger than corresponding moving average rule returns in all countries, which is in line with results for Asian countries, and very substantial compared with the zero return strategy of always being out of the market. In addition, average buy-sell differences far exceed the unconditional 10-day returns. Particularly interesting is the trading rule outcome for Chile, with an annualized buy-sell difference equal to about 100%, which is roughly nine times the buy-and-hold average. Moreover, this rate of return even exceeds the corresponding average of two Asian countries, Thailand and Taiwan.

Finally, we evaluate the trading rule profits by the alternative benchmark strategy of holding a long position in the market index and superimposing the trading signals on the index (explained in the previous subsection). Of the rules that produce significant buy-sell statistics, the (1,50,0) and (1,50,0.01) TRB rules in Brazil generate annual rates of return of 26.8 pecent and 17.8 percent respectively with this strategy, which compare with an annualized buy-and-hold return of 12%. The (1,50,0) rule in Mexico yields a lower return than the unconditional average (15.8 versus 20.0 percent). In the case of Chile, the two faster TRB rules yield returns higher than the average buy-and-hold return - 16.3 and 12.7 percent -, while the (1,200,0.01) rule generates the same annualized return as the buy-and-hold (11.4 percent). Considering transaction

[31] Our results for the Latin American markets are consistent with Urrutia (1995), who examines the random walk hypothesis in the case of Brazil, Argentina, Mexico, and Chile. He concludes that the hypothesis should be rejected for the Chilean stock market which shows a substantially slower adjustment to information shocks as compared to United States and European markets. This is explained by the low liquidity of Chilean markets and infrequent trading.

costs and the frequency of trading, only the (1,50,0) rule in Brazil can possibly generate returns over and above the 12% benchmark. And with an average of 10.2 signals per annum, excess returns can only be realized with a rather conservative estimate for transaction costs of up to 1.45% per trade. Therefore, although trading rules produce economically meaningful signals as with Asian markets, it seems that from a trader's point of view it is much harder to beat the market in Latin America than Asia.

4.4 Boorstrap test results

We generate 1000 bootstrap samples per country for sample lengths of 3761 corresponding to the market index sample lengths, using the estimated econometric models and methodology of section 3.4, and apply each TRB and moving average rule to the boostrap samples. Utilizing the bootstrap distributions of the estimated models for each country allows us to evaluate the significance of the trading rule results with return ditributions that deviate from normality. Table V presents the summary statistics for the simulated models for each country. The table shows the average mean, variance, skewness and kurtosis across the 1000 simulations, as well as the standard deviations of these estimates. The results for the mean and variance of the simulated series are reasonably close with the actual series in all markets from tables Ia and Ib, given the precision (standard deviation); this is not surprising since the conditional mean and variance processes of the simulated series were obtained from the stock returns series. Perhaps more surprising is the close agreement among the other moments, since no explicit matching was done for any of these individually. In all markets, the estimated skewness and kurtosis values are different from their respective Gaussian values, and given their precision, are not significantly different from the values of the actual returns. Argentina is a notable exception, with actual skewness and kurtosis figures far bigger than those of the simulated series (though the simulated skewness and kurtosis are in the right direction).

4.4.1 Asian Markets

In tables IIIa-d and IVa-d, Panels B and C, we display the results of the boostrap simulations for both moving average and TRB rules for the Asian markets. Panel B refers to results from individual rules, while in Panel C results are summarized across all rules using a simple average, in order to jointly test our set of trading rules. All the numbers refer to the fraction of the simulated series producing a test statistic bigger than that of the original series, and can thus be regarded as simulated "p-values". The statistics of interest are average buy and sell returns, buy-sell return, and standard deviations of buy and sells.[32] We will mostly base

[32] A p-value less than 0.05 or bigger than 0.95 indicates that, at the 5% significance level, the null hypothesis that the statistic of interest is equivalent in both the actual series and the simulated model can be rejected. As such, the trading rule statistics act also as a specification test for the preferred model.

our discussion on Panel C, since average results convey the overall picture and are consistent with individual rule results. The second row of Panel C, labelled Mean, presents the returns and standard deviations for the buys, sells, and buy-sells, averaged over the 1000 simulated series. The third row, labeled with each country's name, presents the same statistics for the MSCI market index series.

Starting with moving average rules, trading results seem to be broadly consistent with traditional tests, though when one considers significance relative to the simulated models, returns are not as strongly significant as t-statistics have suggested. For example, only the (1,50,0.01) rule tested on the simulated series for Philippines produces buy returns which differ significantly from the actual series (and that only at the 10% level), while t-statistics suggested that four rules produce significant average buy returns. Moreover, t-ratios suggest that sell and buy-sell returns from all rules in Philippines are strongly significant (table IIIa, Panel A), but significance with bootstrap results is supported only at the 10% level for just three rules in the case of sell returns and only four rules in the buy-sells case. This suggests that distributional assumptions play an important role for statistical inferences. Focussing on the rule averages for Philippines in Panel C, we can see that the simulated model is capable of replicating actual buy returns better than actual sell returns. This is not only indicated by the p-values, but also by the fact that average simulated buy returns are closer to the actual buy returns than simulated sells are to the actual sells. The p-value of 0.090 for the average buy-sell difference suggests that at the 10% significance level, the actual buy-sell difference is different from the average simulated value. In addition, the simulated model is better at explaining sell standard deviations (p-value of 0.340 and mean simulated sell standard deviation very close to the value from the actual series) than buy standard deviations (even though the average p-value of 0.866 does not reject the underlying econometric model), which thing can also be observed from individual rule results.

In the case of Taiwan, there is greater agreement between standard and bootstrap tests, which is not surprising given that the deviation from normality in the stock index returns series is not as large as in the other countries (as revealed by the skewness and kurtosis figures in Table V), and the moments of the bootsrapped returns series are quite close to the actual values. Therefore, simulated sell and buy-sell returns across almost all rules are significantly different from the actual values, most even at the 5% significance level, while, as indicated by t-statistics as well, only the buy returns from the first two rules are significant. Concentrating on rules averages, the p-value of 0.036 for the buy-sell statistic shows that trading rule returns are also significant relative to the simulated model; the generated stock returns series cannot produce as large a buy-sell spread as the Taiwan series. As far as standard deviations are concerned, the buy volatilities are very well captured by the simulations (p-value of 0.450), with a mean value almost equal to the actual, while this is not so for sell volatilities; however, the discrepancy is only significant at the 10% level. The simulated buy and sell volatilities are almost equal (as the mean values from the rules average reveal), while in fact sell returns in the actual series appear to be more volatile than buy returns. This is also the case for Philippines.

As far as simulated moving average rule results in Thailand are concerned, only the two faster rules produce significant buy and sell returns, in agreement with standard test inferences; (sell returns of some other rules are weakly significant with t-statistics, insignificant with bootstrap tests). Moreover, only the former two rules' actual buy-sell returns seem to be significant relative to the simulated model; buy-sell returns of other rules are better replicated by the simulations, and do no agree with the significant t-ratios. P-values reveal no significant difference between actual and simulated buy and sell volatilities, however, they show that the buy stdev. is better described by the model. Also, the mean simulated values do not produce a spread between the two volatilites, as is actually the case with sell returns having a higher average volatility than buy returns. Similar results for buy and sell volatilities are obtained in the case of Indonesia, while the statistical significance of trading rule returns evaluated with both standard and bootstrap tests is, for almost all rules, in agreement. The all-rules average simulated p-value of 0.066 for the buy-sell statistic indicates that the specified econometric model cannot produce on average a buy-sell spread as large as the original , and is significantly different from it at the 10% level.

The TRB rule bootstrap results are also in line with standard statistical tests for all countries. The trading rule returns which are strongly significant using t-statistics are also significant relative to the simulated distribution (and those which are insignificant according to standard tests are also insignificantly different from the simulated returns according to p-values). There are only very few exceptions to this pattern, and one case is the Philippines (1,150,0.01) rule which generates a significantly different from zero buy-sell spread, however not significantly different from the simulated distribution (p-value of 0.194). On average (Panel C of tables IVa-d), the simulated models cannot produce the buy-sell spread observed with actual data in the cases of Philippines, Taiwan, and Indonesia, with results that strongly reject the null of equal rule returns in actual and simulated series, even at the 5 percent level. Consequently, rejections are stronger for the TRB than the moving average rules. With regards to volatility of buy and sell returns, the preferred model for Philippines is very successful since it produces values for buy and sell standard deviations very close to the true values (and a mean sell stdev. higher than the corresponding buy stdev.). Although even at the 10% significance level we cannot reject the hypothesis that buy and sell volatilites an Thailand and Indonesia are not significantly different from the corresponding simulated values, the average simulated sell volatility is lower than the buy volatility, in contrast with actual data. In Taiwan the p-value for the average sell volatility is 0.048.

For the most part, the results of the bootstrap tests for returns are consistent with traditional tests presented earlier. Trading rules that produce excess returns using the strategy of section 4.3.1, even after accounting for transaction costs, are also confirmed to generate significant trading outcomes with the bootstrap tests. The underlying null econometric models do not do a bad job of replicating buy and sell volatilities according to the p-values, although the simulated averages do not reflect the fact that sell standard deviations exceed buy standard deviations in the actual data. However, that sell returns are more volatile than buy returns in all Asian markets is also borne out by the fact that buy stdev. p-values for each rule, and on average, are (almost always) much higher than corresponding p-values for sell return volatility. Therefore, buy signals do not only select out periods with higher conditional means than sell signals, but also pick periods with lower volatilities! This observation has also been made by Brock et al (1992) using their long US data set. Aside from the negative returns during sell periods being incosistent with time-varying risk premia explanations for return predictability, the fact that these returns arise in riskier periods than the higher average buy returns render this explanation all the more problematic. Finally, it is very interesting to observe that average buy returns volatility across all rules is very comparable with the unconditional volatility of each market from Table Ia. This means that the positive buy returns, which exceed the buy-and-hold return by a number of times, do not come at the expense of higher risk. Even though sell returns individually appear more risky than buy-and-hold returns, our trading strategy that utilizes both buy and sell returns, yielding outcomes many times the unconditional return in each market, should not be much more volatile than the buy-and-hold.

4.4.2 Latin American Markets

Tables IIIe-h and IVe-h, Panels B and C, report the bootstrap test results for moving average and TRB rules respectively. The presentation of results follows the same format as in Asian countries. In Brazil, Mexico, and Argentina, the simulated null models seem to do a very good job of capturing and replicating conditional mean and volatility dynamics (excluding the TRB rules average buy and sell volatilities in Mexico). This is not only indicated by the simulated p-values for each return and stdev. statistic and rule, but also by the buy, sell, and buy-sell spread returns averaged over the 1000 simulations, which, particularly for the moving average rules in Mexico and Brazil, are very close to the true values for the series. In addition, average simulated sell volatilites for both TRB and moving average rules exceed the average buy volatilities, in agreement with what is observed in the actual data. The few individual trading rule returns that are significant according to t-statistics in the above three countries, appear now to be insignificant relative to the simulated null model; excluded are only the (1,50,0) TRB sell and buy-sell returns in Brazil, which are significant with both measures. In fact, this is the only rule from the Latin American markets that according to the trading strategy in section 4.3.2 can probably generate returns even after transaction costs.

We have left Chile out of the above discussion because the pattern of results for Chile rather resembles that of Asian countries. Market index returns in Chile are more persistent than returns in the other Latin American countries, as reflected by the significant t-ratios of trading rule returns for almost all rule specifications. However, bootstrap test results do not support significance of moving average rule results relative to the simulated AR(2) - FIGARCH(1,δ,0) model for Chile, excluding only the buy returns of the (1,50,0) and (1,50,0.01) rules. Therefore, according to moving average rule results, the underlying model is capable of matching the trading rule statistics; average buy and sell volatilites from the simulations even reflect that in the original series the stdev. of sell returns is only marginally higher than the buy stdev. On the contrary, TRB rule test results are more in line with traditional t-tests, indicating that returns are significant even with the bootstrap test. Panel C of table IVh reports a buy-sell p-value for TRB rule averages of 0.01. Overall, we cannot draw strong conclusions as to the success of the chosen model in describing stock retun dynamics in Chile. Yet it is able to better account for buy and sell return volatilities than it is in replicating rule returns.

Finally, we also observe the phenomenon of buy signals selecting periods of higher conditional returns but lower volatility than sell signals, in agreement with Asian country results. Therefore, we are very sceptical about a changing risk levels explanation of predictability in Latin American markets, as we are about Asian markets. It should also be noted that, as for Asian markets, conditional buy returns for both types of rules usually have a lower volatility than unconditional returns, while sell return volatility is higher than the buy-and-hold volatility, in some cases much so (eg. TRB rules average sell volatility in Mexico, Brazil and Chile). Actually, relative to unconditional sell standard deviations for each country, Latin American markets seem to have more volatile sell returns than Asian markets. With the Brock et al trading strategy, only the (1,50,0) rule in Chile and Brazil and the (1,50,0.01) rule in Chile produce higher than buy-and-hold returns; however, since the margin in the case of Chile is relatively small even before considering transaction costs, perhaps it is not prudent to tolerate higher risk and trade.

5 Conclusion

In this paper we have carried out a comprehensive study of the returns generating process and profitability of technical trading rules in ECM, notably four Asian and four Latin American countries. Using daily data since 1988 for all eight countries, we have concluded that the dollar denominated returns generating process exhibits significant long memory effects in the volatility but not in the mean. "Trading" upon such findings, moving average and trading range break rules outperform the simple "buy-and-hold" strategy for all markets, and after allowing for a threshold transaction cost of 2 percent, we find that it is still possible to make significant excess returns with some of the trading rules in Asian markets. The significance of our results is reinforced by bootstrap simulations of the "favorite" returns generating model.

In contrast to previous studies in developed markets, we document significant predictive ability of our simple trading rules, particularly in Asian markets, using a relatively short span of data. The robustness of our results cast doubt on the weak form efficiency of ECM.

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T able Ia: Summary Statistics for Daily and 10-Day Returns in Asian Markets

Returns are measured as log differences of the level of the MSCI index for each country over the full sample. 10-day returns are based on 10-day nonoverlapping periods. $\rho(i)$ is the estimated autocorrelation coefficient at lag i for each series. Numbers marked with ** are significant at the 5% level for a two-tailed test. The Barlett standard error is calculated as $1.96/\sqrt{N}$, where N is the sample length.

Panel A: Daily Returns				
	Philippines	Taiwan	Thailand	Indonesia
1-day Mean	0.000056 (1.5%)	0.000194 (5.1%)	-0.000043 (-1.1%)	0.000048(1.3%)
Stdev.	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**	0.0631**	0.1886**	0.1907**
$\rho(2)$	0.0098	0.0454**	0.0297	0.0661**
$\rho(3)$	-0.0029	0.0430**	-0.0163	-0.0231
$\rho(4)$	0.0056	-0.0183	0.0119	-0.0782**
$\rho(5)$	-0.0281	0.0045	-0.0446**	0.0130
$\rho(10)$	0.0282	0.0196	0.0428**	0.0624**
$\rho(100)$	-0.0224	0.0177	-0.0009	0.0213
Autocorrelation Statistics for daily squared returns				
$\rho(1)$	0.1657**	0.1677**	0.2143**	0.2719**
$\rho(2)$	0.0897**	0.2902**	0.1927**	0.1278**
$\rho(3)$	0.0900**	0.1833**	0.2627**	0.1653**
$\rho(4)$	0.0467**	0.1983**	0.0932**	0.1890**
$\rho(5)$	0.0689**	0.1692**	0.1312**	0.1960**
$\rho(10)$	0.0707**	0.2783**	0.1732**	0.1072**
$\rho(100)$	0.0234	0.0912**	0.0509**	0.0360**
Barlett standard error = 0.0320				
Panel B: 10-Day Returns				
Mean	0.00056	0.0019	-0.00043	0.00048
Stdev.	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

TABLE Ib: Summary Statistics for Daily and 10-Day Returns in Latin American Markets

Returns are measured as log differences of the level of the MSCI index for each country over the full sample. 10-day returns are based on 10-day nonoverlapping periods. $\rho(i)$ is the estimated autocorrelation coefficient at lag i for each series. Numbers marked with ** are significant at the 5% level for a two-tailed test. The Barlett standard error is calculated as $1.96/\sqrt{N}$, where N is the sample length.

Panel A: Daily Returns				
	Mexico	Brazil	Argentina	Chile
Mean	0.000766 (20.0%)	0.000463 (12.0%)	0.000305 (8.0%)	0.000439 (11.4%)
Std.	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**	0.1473**	-0.0309	0.2287**
$\rho(2)$	-0.0160	0.0563**	-0.1461**	0.0390**
$\rho(3)$	0.0086	0.0316	0.0697**	-0.0135
$\rho(4)$	0.0153	0.0159	-0.0094	0.0121
$\rho(5)$	0.0107	0.0147	-0.0493**	0.0355**
$\rho(10)$	0.0455**	0.0097	0.0210	0.0435**
$\rho(100)$	0.0157	0.0293	0.0113	0.0094
Autocorrelation Statistics for daily squared returns				
$\rho(1)$	0.2591**	0.2722**	0.0773**	0.1045**
$\rho(2)$	0.1375**	0.2310**	0.1907**	0.0748**
$\rho(3)$	0.1365**	0.1965**	0.0235**	0.1022**
$\rho(4)$	0.0922**	0.0949**	0.0556**	0.0391**
$\rho(5)$	0.1142**	0.0846**	0.0897**	0.0459**
$\rho(10)$	0.0991**	0.1678**	0.0991**	0.0385**
$\rho(100)$	-0.0044	0.0234	0.0065	-0.0059
Barlett standard error = 0.0320				
Panel B: 10-Day Returns				
Mean	0.00766	0.00463	0.00305	0.00439
Stdev.	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

TABLE IIa: Esimated Models for Philippines Daily Returns

	AR(1)-GARCH(1,1)	AR(1)-IGARCH(1,1)	AR(1)-FIGARCH(1,δ,1)	AR(1)-FIGARCH(1,δ,0)
μ	0.0515* (0.028)	0.0558* (0.029)	0.0538* (0.030)	0.0485* (0.0275)
ρ_1	0.1764*** (0.018)	0.1761*** (0.019)	0.1805*** (0.018)	0.1835*** (0.018)
ω	0.0998*** (0.020)	0.0688*** (0.013)	0.1468*** (0.026)	0.1879*** (0.032)
α	0.1295*** (0.015)	0.1428*** (0.016)	-	-
β	0.8478*** (0.018)	-	0.5518*** (0.061)	0.5443*** (0.1070)
ϕ	-	-	0.1390*** (0.047)	-
δ	-	-	0.5244*** (0.073)	0.6357*** (0.112)
$\ln(L)$	-6966.259	-6970.712	-6954.258	-6959.350
AIC	13942.517	13949.425	13920.517	13928.700
SBC	13950.393	13955.726	13929.968	13936.576
Skewness	1.194	1.240	1.268	1.282
Kurtosis	26.816	27.459	25.871	25.878
$Q(100)$	92.011	92.576	89.949	89.964
$Q^2(100)$	30.120	29.906	22.558	23.435

Note: The daily returns series is from January 1, through May 14, 2002; a total of 3760 observations. Results are for returns $\times 100$. Only parsimonious in-the-mean models are presented. QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. The quantity $\ln(L)$ is the value of the maximized log likelihood. The sample skewness and kurtosis refer to the standardized residuals. The $Q(100)$ and $Q^2(100)$ statistics are the Ljung-Box test statistics for 100 degrees of freedom to test for serial correlation in the standardized and squared standardized residuals.

TABLE IIb: Esimated Models for Taiwan Daily Returns

	AR(3)-GARCH(1,1)	AR(3) -IGARCH(1,1)	AR(3)-FIGARCH(1,δ,1)	AR(3)-FIGARCH(1,δ,0)
μ	0.0567 (0.043)	0.0582 (0.046)	0.0705** (0.035)	0.0704*** (0.039)
ρ_1	0.0473** (0.021)	0.0461*** (0.017)	0.048*** (0.018)	0.0477*** (0.018)
ρ_2	0.0401* (0.022)	0.0402*** (0.016)	0.0413*** (0.017)	0.0414** (0.018)
ρ_3	0.0390** (0.018)	0.0397** (0.0185)	0.0339** (0.017)	0.0339** (0.018)
ω	0.0819*** (0.020)	0.0367*** (0.009)	0.3604*** (0.060)	0.3474*** (0.059)
α	0.0693*** (0.009)	0.0764*** (0.009)	-	-
β	0.9115*** (0.012)	-	0.2537*** (0.042)	0.2721*** (0.037)
ϕ	-	-	-0.0156 (0.017)	-
δ	-	-	0.3198*** (0.032)	0.3231*** (0.059)
$\ln(L)$	-7792.551	-7804.516	-7791.280	-7791.289
AIC	15599.103	15621.032	15598.560	15596.578
SBC	15610.129	15630.483	15611.162	15607.604
Skewness	-0.038	-0.041	-0.034	-0.035
Kurtosis	4.578	4.825	4.667	4.671
$Q(100)$	107.247	105.079	109.653	109.538
$Q^2(100)$	162.561	164.873	145.014	144.928

Note: The daily returns series is from January 1, through May 14, 2002; a total of 3760 observations. Results are for returns $\times 100$. Only parsimonious in-the-mean models are presented. QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. The quantity $\ln(L)$ is the value of the maximized log likelihood. The sample skewness and kurtosis refer to the standardized residuals. The $Q(100)$ and $Q^2(100)$ statistics are the Ljung-Box test statistics for 100 degrees of freedom to test for serial correlation in the standardized and squared standardized residuals.

TABLE IIc: Esimated Models for Thailand Daily Returns

	AR(2)-GARCH(1,1)	AR(2)-IGARCH(1,1)	AR(2)-FIGARCH(1,δ,1)	AR(2)-FIGARCH(1,δ,0)
μ	0.0434*** (0.024)	0.0435 (0.042)	0.0375 (0.082)	0.0373 (0.030)
ρ_1	0.1538*** (0.018)	0.1538*** (0.018)	0.1545*** (0.019)	0.1551*** (0.019)
ρ_2	0.0555*** (0.019)	0.0561*** (0.018)	0.0533*** (0.019)	0.0541** (0.018)
ω	0.0694*** (0.013)	0.0624*** (0.011)	0.1695*** (0.060)	0.2085*** (0.038)
α	0.1273*** (0.012)	0.1338*** (0.012)	-	-
β	0.8663*** (0.012)	-	0.3256*** (0.167)	0.2027*** (0.036)
ϕ	-	-	0.1107 (0.153)	-
δ	-	-	0.3792*** (0.039)	0.3614*** (0.031)
$\ln(L)$	-7498.260	-7498.958	-7458.897	-7459.227
AIC	15008.520	15007.916	14931.795	14930.455
SBC	15017.971	15015.792	14942.821	14939.906
Skewness	0.168	0.167	0.133	0.131
Kurtosis	7.756	7.775	6.733	6.755
$Q(100)$	128.883	128.155	132.375	132.910
$Q^2(100)$	101.481	98.861	98.743	98.434

Note: The daily returns series is from January 1, through May 14, 2002; a total of 3760 observations. Results are for returns $\times 100$. Only parsimonious in-the-mean models are presented. QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. The quantity $\ln(L)$ is the value of the maximized log likelihood. The sample skewness and kurtosis refer to the standardized residuals. The $Q(100)$ and $Q^2(100)$ statistics are the Ljung-Box test statistics for 100 degrees of freedom to test for serial correlation in the standardized and squared standardized residuals.

TABLE IId: Esimated Models for Indonesian Daily Returns

	AR(2)-GARCH(1,1)	AR(2)-IGARCH(1,1)	AR(2)-FIGARCH(1,δ,1)	AR(2)-FIGARCH(1,δ,0)
μ	0.0660*** (0.023)	0.0537** (0.024)	0.0361 (0.028)	0.0348 (0.030)
ρ_1	0.1767*** (0.020)	0.1807*** (0.020)	0.2107*** (0.021)	0.2004*** (0.021)
ρ_2	0.0468*** (0.017)	0.0516*** (0.019)	0.0363** (0.020)	0.0433** (0.023)
ω	0.0795*** (0.011)	0.1063*** (0.011)	0.2074*** (0.036)	0.1491*** (0.025)
α	0.3637*** (0.028)	0.2460*** (0.014)	-	-
β	0.7222*** (0.015)	-	-0.1482*** (0.073)	0.1785*** (0.036)
ϕ	-	-	-0.1012 (0.153)	-
δ	-	-	0.4769*** (0.023)	0.4912*** (0.029)
$\ln(L)$	-7276.171	-7299.934	-7215.264	-7208.886
AIC	14564.342	14609.868	14442.527	14431.772
SBC	14573.793	14617.744	14451.978	14442.798
Skewness	0.777	0.803	0.491	0.574
Kurtosis	14.772	14.951	11.617	12.173
$Q(100)$	172.643	165.353	158.325	159.512
$Q^2(100)$	339.638	345.385	190.675	197.695

Note: The daily returns series is from January 1, through May 14, 2002; a total of 3760 observations. Results are for returns $\times 100$. Only parsimonious in-the-mean models are presented. QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. The quantity $\ln(L)$ is the value of the maximized log likelihood. The sample skewness and kurtosis refer to the standardized residuals. The $Q(100)$ and $Q^2(100)$ statistics are the Ljung-Box test statistics for 100 degrees of freedom to test for serial correlation in the standardized and squared standardized residuals.

TABLE IIe: Esimated Models for Mexico Daily Returns

	AR(1)-GARCH(1,1)	AR(1)-IGARCH(1,1)	AR(1)-FIGARCH(1,δ,1)	AR(1)-FIGARCH(1,δ,0)
μ	0.1566*** (0.030)	0.1623*** (0.030)	0.1522*** (0.029)	0.1532*** (0.029)
ρ_1	0.1840*** (0.018)	0.1870*** (0.018)	0.1800*** (0.019)	0.1789*** (0.018)
ω	0.2418*** (0.034)	0.1577*** (0.025)	0.3603*** (0.053)	0.3286*** (0.048)
α	0.1805*** (0.018)	0.2249*** (0.022)	-	-
β	0.7567*** (0.022)	-	0.0506 (0.050)	0.1313*** (0.046)
ϕ	-	-	-0.0803 (0.067)	-
δ	-	-	0.3490*** (0.037)	0.3563*** (0.040)
$\ln(L)$	-7267.101	-7285.586	-7249.481	-7249.668
AIC	14544.203	14579.172	14510.961	14509.337
SBC	14552.079	14585.473	14520.412	14517.213
Skewness	-0.412	-0.458	-0.415	-0.418
Kurtosis	6.752	7.014	6.501	6.529
$Q(100)$	103.259	103.419	103.837	103.958
$Q^2(100)$	91.542	77.737	73.907	74.049

Note: The daily returns series is from January 1, through May 14, 2002; a total of 3760 observations. Results are for returns $\times 100$. Only parsimonious in-the-mean models are presented. QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. The quantity $\ln(L)$ is the value of the maximized log likelihood. The sample skewness and kurtosis refer to the standardized residuals. The $Q(100)$ and $Q^2(100)$ statistics are the Ljung-Box test statistics for 100 degrees of freedom to test for serial correlation in the standardized and squared standardized residuals.

TABLE IIf: Esimated Models for Brazil Daily Returns

	AR(1)-GARCH(1,1)	AR(1)-IGARCH(1,1)	AR(1)-FIGARCH(1,δ,1)	AR(1)-FIGARCH(1,δ,0)
μ	0.1034*** (0.037)	0.1030*** (0.040)	0.1039*** (0.039)	0.1037*** (0.039)
ρ_1	0.1426*** (0.018)	0.1427*** (0.018)	0.1454*** (0.018)	0.1475*** (0.017)
ω	0.0675*** (0.020)	0.0768*** (0.016)	0.1522*** (0.045)	0.2507*** (0.056)
α	0.1193*** (0.011)	0.1162*** (0.010)	-	-
β	0.8843*** (0.010)	-	0.6008*** (0.061)	0.3872*** (0.052)
ϕ	-	-	0.1514*** (0.037)	-
δ	-	-	0.5538*** (0.064)	0.4650*** (0.048)
$\ln(L)$	-8759.269	-8759.537	-8752.786	-8759.611
AIC	17528.538	17527.075	17517.571	17529.222
SBC	17536.414	17533.375	17527.022	17537.098
Skewness	-0.510	-0.512	-0.580	-0.615
Kurtosis	6.492	6.530	7.040	7.457
$Q(100)$	107.233	106.991	106.832	106.934
$Q^2(100)$	98.525	97.978	82.286	91.326

Note: The daily returns series is from January 1, through May 14, 2002; a total of 3760 observations. Results are for returns $\times 100$. Only parsimonious in-the-mean models are presented. QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. The quantity $\ln(L)$ is the value of the maximized log likelihood. The sample skewness and kurtosis refer to the standardized residuals. The $Q(100)$ and $Q^2(100)$ statistics are the Ljung-Box test statistics for 100 degrees of freedom to test for serial correlation in the standardized and squared standardized residuals.

TABLE IIg: Esimated Models for Argentina Daily Returns

	AR(3)-GARCH(1,1)	AR(3)-IGARCH(1,1)	AR(3)- FIGARCH(1,δ,1)	AR(3)-FIGARCH(1,δ,0)
μ	0.0770** (0.036)	0.0763** (0.037)	0.0778** (0.036)	0.0834** (0.039)
ρ_1	0.0910*** (0.019)	0.0911*** (0.018)	0.0935*** (0.018)	0.0935*** (0.018)
ρ_2	-0.0477*** (0.017)	-0.0476*** (0.018)	-0.0474*** (0.017)	-0.0477*** (0.017)
ρ_3	0.0395** (0.018)	0.0389* (0.020)	0.0395** (0.018)	0.0414** (0.018)
ω	0.0781*** (0.016)	0.0875*** (0.014)	0.1422*** (0.026)	0.1411*** (0.031)
α	0.1317*** (0.011)	0.1253*** (0.090)	-	-
β	0.8739*** (0.009)	-	0.7461*** (0.035)	0.7944*** (0.039)
ϕ	-	-	0.1138*** (0.035)	-
δ	-	-	0.7677*** (0.050)	0.7903*** (0.048)
$\ln(L)$	-8994.761	-8995.496	-8987.666	-8993.252
AIC	18003.522	18002.993	17991.333	18000.504
SBC	18014.549.	18012.444	18003.934	18011.530
Skewness	-0.257	-0.255	-0.255	-0.244
Kurtosis	6.728	6.751	6.721	6.712
$Q(100)$	122.803	122.589	120.706	121.300
$Q^2(100)$	110.441	111.168	106.949	113.827

Note: The daily returns series is from January 1, through May 14, 2002; a total of 3760 observations. Results are for returns $\times 100$. Only parsimonious in-the-mean models are presented. QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. The quantity $\ln(L)$ is the value of the maximized log likelihood. The sample skewness and kurtosis refer to the standardized residuals. The $Q(100)$ and $Q^2(100)$ statistics are the Ljung-Box test statistics for 100 degrees of freedom to test for serial correlation in the standardized and squared standardized residuals.

TABLE IIh: Esimated Models for Chile Daily Returns

	AR(2)-GARCH(1,1)	AR(2)-IGARCH(1,1)	AR(2)-FIGARCH(1,δ,1)	AR(2)-FIGARCH(1,δ,0)
μ	0.0168 (0.014)	0.0157 (0.024)	0.0128 (0.015)	0.0128 (0.013)
ρ_1	0.2758*** (0.019)	0.2759*** (0.018)	0.2759*** (0.018)	0.2759*** (0.018)
ρ_2	-0.0524*** (0.018)	-0.0535*** (0.018)	-0.0547*** (0.019)	-0.0547*** (0.018)
ω	0.1293*** (0.019)	0.0727*** (0.014)	0.1357*** (0.020)	0.1355*** (0.019)
α	0.2003*** (0.019)	0.2266*** (0.026)	-	-
β	0.7330*** (0.024)	-	0.2483*** (0.054)	0.2495*** (0.046)
ϕ	-	-	-0.0012 (0.021)	-
δ	-	-	0.4338*** (0.045)	0.4340*** (0.044)
$\ln(L)$	-5820.590	-5833.161	-5801.064	-5801.065
AIC	11653.180	11676.322	11616.130	11614.129
SBC	11662.631	11684.198	11627.155	11623.580
Skewness	-0.249	-0.197	-0.388	-0.388
Kurtosis	11.287	11.509	10.608	10.611
$Q(100)$	113.225	111.154	113.827	113.837
$Q^2(100)$	251.291	289.628	141.514	141.498

Note: The daily returns series is from January 1, through May 14, 2002; a total of 3760 observations. Results are for returns $\times 100$. Only parsimonious in-the-mean models are presented. QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. The quantity $\ln(L)$ is the value of the maximized log likelihood. The sample skewness and kurtosis refer to the standardized residuals. The $Q(100)$ and $Q^2(100)$ statistics are the Ljung-Box test statistics for 100 degrees of freedom to test for serial correlation in the standardized and squared standardized residuals.

Table IIIa: Standard and Bootstrap test results for Moving Average Rules - Philippines

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Rules are identified as (fast,slow,band), where fast and slow are the fast (short) and slow (long) moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals respectively. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 1-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages over all rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(1) - FIGARCH(1,δ,1) model. The rows reading fraction>Philip. refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Philippines" represents the actual mean return or standard deviation from the MSCI Philippines series.

Panel A: Trading Rule Results

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	1834	1722	0.002039	-0.002180	0.5414	0.4326	0.004219
			(3.954)	(-4.356)			(7.133)
(1,50,0.01)	1636	1523	0.002305	-0.002291	0.5483	0.4294	0.004595
			(4.313)	(-4.394)			(7.336)
(1,150,0)	1629	1581	0.000956	-0.001412	0.5088	0.4522	0.002366
			(1.723)	(-2.777)			(3.736)
(1,150,0.01)	1550	1511	0.001014	-0.001521	0.5071	0.4520	0.002532
			(1.803)	(-2.935)			(3.978)
(5,150,0)	1638	1580	0.000845	-0.001180	0.5037	0.4582	0.002025
			(1.514)	(-2.346)			(3.265)
(5,150,0.01)	1567	1520	0.000907	-0.001140	0.5054	0.4579	0.002050
			(1.607)	(-2.240)			(3.301)
(1,200,0)	1635	1561	0.000728	-0.001272	0.5019	0.4608	0.001998
			(1.289)	(-2.455)			(3.207)
(1,200,0.01)	1548	1491	0.000751	-0.001272	0.5019	0.4608	0.002021
			(1.307)	(-2.455)			(3.159)
Average			0.001193	-0.001533			0.002725
Annualized			31%	-40%			71%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	fraction>Philip.	0.110	0.730	0.890	0.416	0.080
(1,50,0.01)	fraction>Philip.	0.095	0.760	0.880	0.400	0.082
(1,150,0)	fraction>Philip.	0.342	0.900	0.898	0.328	0.134
(1,150,0.01)	fraction>Philip.	0.326	0.886	0.910	0.322	0.112
(5,150,0)	fraction>Philip.	0.168	0.914	0.934	0.348	0.060
(5,150,0.01)	fraction>Philip.	0.154	0.906	0.924	0.340	0.065
(1,200,0)	fraction>Philip.	0.478	0.920	0.880	0.316	0.182
(1,200,0.01)	fraction>Philip.	0.474	0.908	0.872	0.322	0.200

Panel C: Bootstrap test results, Rule Averages

	Fraction>Philip.	0.204	0.866	0.900	0.340	0.090
	Mean	0.000859	0.022461	-0.000791	0.021759	0.001653
	Philippines	0.001193	0.014194	-0.001531	0.020805	0.002725

Table IIIb: Standard and Bootstrap test results for Moving Average Rules - Taiwan

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Rules are identified as (fast,slow,band), where fast and slow are the fast (short) and slow (long) moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals respectively. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 1-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages over all rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(3) - FIGARCH(1,δ,0) model. The rows reading fraction>Taiwan refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Taiwan" represents the actual mean return or standard deviation from the MSCI Taiwan series.

Panel A: Standard Test Results for the Moving Average Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	1653	1772	0.001925 (2.739)	-0.001931 (-3.444)	0.5130	0.4283	0.003856 (5.266)
(1,50,0.01)	1483	1599	0.001996 (2.745)	-0.002076 (-3.551)	0.5158	0.4219	0.004073 (5.275)
(1,150,0)	1758	1724	0.001126 (1.507)	-0.001288 (-2.380)	0.5028	0.4345	0.002414 (3.326)
(1,150,0.01)	1680	1631	0.001194 (1.432)	-0.001247 (-2.269)	0.5036	0.4365	0.002341 (3.145)
(5,150,0)	1738	1733	0.000836 (1.034)	-0.000933 (-1.842)	0.4965	0.4403	0.001769 (2.433)
(5,150,0.01)	1662	1648	0.000966 (1.289)	-0.001050 (-1.985)	0.4960	0.4402	0.002016 (2.767)
(1,200,0)	1697	1632	0.000919 (1.157)	-0.001091 (-2.025)	0.4968	0.4363	0.002010 (2.707)
(1,200,0.01)	1548	1491	0.000751 (1.307)	-0.001272 (-2.455)	0.5019	0.4608	0.002021 (3.159)
Average			0.001232	-0.001321			0.002553
Annualized			32%	-35%			67%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	fraction>Taiwan	0.070	0.400	0.956	0.090	0.040
(1,50,0.01)	fraction>Taiwan	0.096	0.378	0.950	0.078	0.044
(1,150,0)	fraction>Taiwan	0.210	0.426	0.940	0.096	0.048
(1,150,0.01)	fraction>Taiwan	0.280	0.408	0.922	0.096	0.084
(5,150,0)	fraction>Taiwan	0.152	0.458	0.956	0.108	0.026
(5,150,0.01)	fraction>Taiwan	0.098	0.468	0.938	0.098	0.022
(1,200,0)	fraction>Taiwan	0.264	0.520	0.910	0.094	0.086
(1,200,0.01)	fraction>Taiwan.	0.356	0.506	0.910	0.092	0.102

Panel C: Bootstrap test results, Rule Averages

	Fraction>Taiwan	0.154	0.450	0.948	0.092	0.036
	Mean	0.000881	0.019074	-0.000621	0.019440	0.001503
	Taiwan	0.001232	0.018758	-0.001321	0.023804	0.002553

Table IIIc: Standard and Bootstrap test results for Moving Average Rules - Thailand

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Rules are identified as (fast,slow,band), where fast and slow are the fast (short) and slow (long) moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals respectively. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 1-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages over all rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(2) - FIGARCH(1,δ,0) model. The rows reading fraction>Thail. refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Thailand" represents the actual mean return or standard deviation from the MSCI Thailand series.

Panel A: Standard Test Results for the Moving Average Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	1686	1799	0.002154 (3.402)	-0.002350 (-3.652)	0.5297	0.4235	0.004504 (6.0300)
(1,50,0.01)	1514	1657	0.002344 (3.559)	-0.002788 (-4.224)	0.5350	0.4261	0.005131 (6.550)
(1,150,0)	1702	1757	0.000922 (1.500)	-0.001154 (-1.744)	0.5071	0.4536	0.002076 (2.770)
(1,150,0.01)	1586	1654	0.000874 (1.390)	-0.001303 (-1.937)	0.5120	0.4450	0.002177 (2.811)
(5,150,0)	1712	1776	0.000459 (0.782)	-0.000796 (-1.186)	0.4988	0.4566	0.001255 (1.681)
(5,150,0.01)	1592	1660	0.000415 (0.695)	-0.000966 (-1.420)	0.5000	0.4536	0.001380 (1.786)
(1,200,0)	1795	1664	0.000738 (1.235)	-0.001225 (-1.821)	0.5058	0.4471	0.001962 (2.616)
(1,200,0.01)	1685	1552	0.000766 (1.269)	-0.001342 (-2.001)	0.5080	0.4414	0.002118 (2.824)
Average			0.001084	-0.001491			0.002575
Annualized			28%	-39%			67%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	fraction>Thail.	0.068	0.340	0.908	0.142	0.056
(1,50,0.01)	fraction>Thail.	0.070	0.342	0.948	0.152	0.038
(1,150,0)	fraction>Thail.	0.222	0.536	0.664	0.116	0.226
(1,150,0.01)	fraction>Thail.	0.270	0.532	0.744	0.110	0.236
(5,150,0)	fraction>Thail.	0.186	0.536	0.716	0.130	0.162
(5,150,0.01)	fraction>Thail.	0.224	0.518	0.800	0.122	0.140
(1,200,0)	fraction>Thail.	0.258	0.590	0.788	0.110	0.196
(1,200,0.01)	fraction>Thail.	0.270	0.580	0.830	0.104	0.174

Panel C: Bootstrap test results, Rule Averages

	Fraction>Thail.	0.138	0.492	0.846	0.126	0.100
	Mean	0.000589	0.020478	-0.001069	0.019535	0.001658
	Thailand	0.001084	0.018487	-0.001491	0.025698	0.002575

Table IIId: Standard and Bootstrap test results for Moving Average Rules - Indonesia

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Rules are identified as (fast,slow,band), where fast and slow are the fast (short) and slow (long) moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals respectively. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 1-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages over all rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(2) - FIGARCH(1,δ,0) model. The rows reading fraction>Indon. refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Indonesia" represents the actual mean return or standard deviation from the MSCI Indonesia series.

Panel A: Standard Test Results for the Moving Average Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	1810	1711	0.002862 (3.392)	-0.003079 (-3.698)	0.5436	0.4278	0.005941 (6.075)
(1,50,0.01)	1657	1575	0.002904 (3.339)	-0.003368 (-3.924)	0.5470	0.4210	0.006272 (6.145)
(1,150,0)	1339	1684	0.001170 (1.215)	-0.002045 (-2.462)	0.5176	0.4531	0.003239 (3.028)
(1,150,0.01)	1254	1616	0.001118 (1.131)	-0.002058 (-2.442)	0.5215	0.4499	0.003176 (2.910)
(5,150,0)	1346	1698	0.000919 (0.945)	-0.001712 (-2.075)	0.5097	0.4588	0.002631 (2.485)
(5,150,0.01)	1258	1611	0.000923 (0.926)	-0.001627 (-1.940)	0.5151	0.4569	0.002550 (2.337)
(1,200,0)	1291	1735	0.001236 (1.269)	-0.002085 (-2.468)	0.5259	0.4496	0.003264 (3.062)
(1,200,0.01)	1192	1658	0.001297 (1.296)	-0.002085 (-2.495)	0.5277	0.4475	0.003383 (3.071)
Average			0.001554	-0.002250			0.003807
Annualized			40%	-59%			99%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	fraction>Indon.	0.084	0.264	0.922	0.124	0.066
(1,50,0.01)	fraction>Indon.	0.108	0.280	0.918	0.120	0.074
(1,150,0)	fraction>Indon.	0.198	0.504	0.908	0.100	0.106
(1,150,0.01)	fraction>Indon.	0.252	0.512	0.904	0.100	0.128
(5,150,0)	fraction>Indon.	0.114	0.526	0.946	0.108	0.038
(5,150,0.01)	fraction>Indon.	0.126	0.520	0.934	0.108	0.050
(1,200,0)	fraction>Indon.	0.150	0.474	0.934	0.114	0.076
(1,200,0.01)	fraction>Indon.	0.146	0.462	0.932	0.102	0.080

Panel C: Bootstrap test results, Rule Averages

	Fraction>Indon.	0.126	0.426	0.924	0.108	0.066
	Mean	0.000855	0.024900	-0.001112	0.023508	0.001891
	Indonesia	0.001554	0.020631	-0.002250	0.035182	0.003807

Table IIIe: Standard and Bootstrap test results for Moving Average Rules - Mexico

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Rules are identified as (fast,slow,band), where fast and slow are the fast (short) and slow (long) moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals respectively. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 1-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages over all rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(1) - FIGARCH(1,δ,0) model. The rows reading fraction>Mex. refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Mexico" represents the actual mean return or standard deviation from the MSCI Mexico series.

Panel A: Standard Test Results for the Moving Average Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	2189	1359	0.001981	-0.001210	0.5391	0.4683	0.003190
			(2.277)	(-3.144)			(4.654)
(1,50,0.01)	2002	1193	0.002274	-0.001581	0.5460	0.4593	0.003850
			(2.747)	(-3.564)			(5.316)
(1,150,0)	2275	1129	0.001241	-0.000312	0.5266	0.4889	0.001553
			(0.901)	(-1.601)			(2.149)
(1,150,0.01)	2196	1052	0.001271	-0.000332	0.5264	0.4857	0.001603
			(0.948)	(-1.586)			(2.155)
(5,150,0)	2260	1146	0.000991	0.000162	0.5221	0.4974	0.000829
			(0.455)	(-0.902)			(1.151)
(5,150,0.01)	2199	1072	0.001112	0.000186	0.5257	0.5784	0.00093
			(0.657)	(-0.845)			(1.258)
(1,200,0)	2351	1014	0.000956	0.000015	0.5202	0.5000	0.000941
			(1.289)	(-1.071)			(1.263)
(1,200,0.01)	2243	920	0.000918	-0.000092	0.5198	0.4946	0.001012
			(0.286)	(-1.176)			(1.300)
Average			0.001343	-0.000396			0.001740
Annualized			35%	-10%			45%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Mex.	0.422	0.820	0.814	0.134	0.208
(1,50,0.01)	Fraction>Mex.	0.268	0.832	0.858	0.126	0.142
(1,150,0)	Fraction>Mex.	0.700	0.830	0.634	0.138	0.460
(1,150,0.01)	Fraction>Mex.	0.706	0.844	0.594	0.128	0.490
(5,150,0)	Fraction>Mex.	0.592	0.646	0.720	0.164	0.352
(5,150,0.01)	Fraction>Mex.	0.510	0.682	0.682	0.156	0.330
(1,200,0)	Fraction>Mex.	0.882	0.734	0.506	0.140	0.710
(1,200,0.01)	Fraction>Mex.	0.912	0.712	0.546	0.140	0.710

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Mex.	0.644	0.772	0.706	0.136	0.358
	Mean	0.001479	0.017828	-0.000126	0.021308	0.001604
	Mexico	0.001343	0.015125	-0.000396	0.025953	0.001740

Table IIIf: Standard and Bootstrap test results for Moving Average Rules - Brazil

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Rules are identified as (fast,slow,band), where fast and slow are the fast (short) and slow (long) moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals respectively. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 1-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages over all rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(1) - FIGARCH(1,δ,1) model. The rows reading fraction>Brazil refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Brazil" represents the actual mean return or standard deviation from the MSCI Brazil series.

Panel A: Standard Test Results for the Moving Average Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	1873	1598	0.002582	-0.00208	0.5291	0.4662	0.004659
			(2.590)	(-2.939)			(4.728)
(1,50,0.01)	1709	1430	0.002764	-0.002419	0.5284	0.4594	0.005183
			(2.726)	(-3.206)			(4.998)
(1,150,0)	1983	1531	0.001318	-0.000719	0.5174	0.4749	0.002037
			(1.065)	(-1.417)			(2.069)
(1,150,0.01)	1919	1467	0.001343	-0.000657	0.5175	0.4744	0.002000
			(1.083)	(-1.258)			(1.993)
(5,150,0)	2001	1531	0.000514	-0.000248	0.5077	0.4807	0.000762
			(0.064)	(-0.810)			(0.776)
(5,150,0.01)	1936	1481	0.000529	-0.000198	0.5077	0.4801	0.000727
			(0.082)	(-0.745)			(0.728)
(1,200,0)	1955	1483	0.000928	-0.000360	0.5161	0.4747	0.001289
			(0.578)	(-0.927)			(1.293)
(1,200,0.01)	1894	1407	0.008460	-0.000252	0.5148	0.4726	0.001097
			(1.307)	(-0.791)			(1.078)
Average			0.001353	-0.000867			0.002219
Annualized			35%	-23%			58%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Brazil	0.246	0.570	0.678	0.444	0.268
(1,50,0.01)	Fraction>Brazil	0.230	0.560	0.722	0.430	0.224
(1,150,0)	Fraction>Brazil	0.596	0.574	0.520	0.454	0.534
(1,150,0.01)	Fraction>Brazil	0.632	0.570	0.462	0.468	0.578
(5,150,0)	Fraction>Brazil	0.200	0.592	0.628	0.472	0.480
(5,150,0.01)	Fraction>Brazil	0.686	0.592	0.550	0.474	0.486
(1,200,0)	Fraction>Brazil	0.778	0.570	0.426	0.496	0.698
(1,200,0.01)	Fraction>Brazil	0.814	0.570	0.368	0.508	0.778

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Brazil	0.574	0.572	0.558	0.470	0.474
	Mean	0.001486	0.030735	-0.001064	0.041192	0.002551
	Brazil	0.001353	0.024938	-0.000867	0.033568	0.002219

Table IIIg: Standard and Bootstrap test results for Moving Average Rules - Argentina

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Rules are identified as (fast,slow,band), where fast and slow are the fast (short) and slow (long) moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals respectively. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 1-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages over all rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(3) - FIGARCH(1,δ,1) model. The rows reading fraction>Argent. refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Argentina" represents the actual mean return or standard deviation from the MSCI Argentina series.

Panel A: Standard Test Results for the Moving Average Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	1851	1697	0.002218 (1.644)	-0.001320 (-1.360)	0.5200	0.4552	0.003542 (2.572)
(1,50,0.01)	1711	1430	0.002182 (1.570)	-0.001607 (-1.556)	0.5175	0.4484	0.003789 (2.649)
(1,150,0)	1788	1635	0.000026 (-0.237)	-0.000848 (-0.950)	0.5075	0.4590	0.000874 (0.623)
(1,150,0.01)	1919	1467	0.000293 (-0.010)	-0.000463 (-0.619)	0.5100	0.4600	0.000756 (0.525)
(5,150,0)	1825	1637	-0.00018 (-0.413)	-0.000226 (-0.438)	0.5011	0.4695	4.8E-05 (0.035)
(5,150,0.01)	1745	1567	-0.000397 (-0.592)	-0.000186 (-0.398)	0.5014	0.4688	-0.000212 (-0.148)
(1,200,0)	1740	1659	0.000947 (0.541)	-0.000626 (-0.769)	0.5146	0.4585	0.001573 (1.117)
(1,200,0.01)	1894	1407	0.000846 (1.307)	-0.000252 (-0.791)	0.5148	0.4726	0.001097 (1.078)
Average			0.000742	-0.000691			0.001433
Annualized			19%	-18%			37%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Argent.	0.296	0.608	0.174	0.568	0.630
(1,50,0.01)	Fraction>Argent.	0.364	0.608	0.218	0.572	0.642
(1,150,0)	Fraction>Argent.	0.872	0.404	0.298	0.564	0.918
(1,150,0.01)	Fraction>Argent.	0.794	0.420	0.156	0.560	0.942
(5,150,0)	Fraction>Argent.	0.648	0.412	0.344	0.536	0.742
(5,150,0.01)	Fraction>Argent.	0.720	0.420	0.326	0.542	0.782
(1,200,0)	Fraction>Argent.	0.428	0.336	0.262	0.546	0.644
(1,200,0.01)	Fraction>Argent.	0.408	0.366	0.298	0.548	0.604

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Argent.	0.596	0.438	0.232	0.544	0.804
	Mean	0.001023	0.048713	-0.002006	0.057250	0.003029
	Argetina	0.000742	0.038646	-0.000691	0.039440	0.001433

Table IIIh: Standard and Bootstrap test results for Moving Average Rules - Chile

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Rules are identified as (fast,slow,band), where fast and slow are the fast (short) and slow (long) moving averages respectively, and band is the percentage difference that is needed to generate a signal. “N(buy)” and “N(sell)” refer to the number of buy and sell signals respectively. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 1-day mean, and buy-sell from zero. “Buy>0” and “Sell>0” are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages over all rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(2) - FIGARCH(1,δ,0) model. The rows reading fraction>Chile refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. “Mean” refers to the average return or standard deviation from the 1000 simulated series, while “Chile” represents the actual mean return or standard deviation from the MSCI Chile series.

Panel A: Standard Test Results for the Moving Average Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	1878	1676	0.001844	-0.001061	0.5357	0.4270	0.002905
			(3.879)	(-4.000)			(6.758)
(1,50,0.01)	1670	1450	0.002075	-0.001150	0.5468	0.4241	0.003226
			(4.342)	(-4.014)			(7.014)
(1,150,0)	1969	1514	0.001056	-0.000433	0.5084	0.4498	0.001489
			(1.730)	(-2.236)			(3.400)
(1,150,0.01)	1841	1361	0.001179	-0.000430	0.5106	0.4489	0.001609
			(2.029)	(-2.145)			(3.512)
(5,150,0)	1791	1521	0.000818	-0.000209	0.4947	0.4629	0.001027
			(1.030)	(-1.665)			(2.300)
(5,150,0.01)	1663	1381	0.000882	-0.000220	0.4955	0.4332	0.000824
			(0.961)	(-1.145)			(1.767)
(1,200,0)	2043	1438	0.001009	-0.000307	0.5071	0.4548	0.001317
			(1.619)	(-1.880)			(2.986)
(1,200,0.01)	1928	1313	0.001094	-0.000365	0.5083	0.4562	0.001460
			(1.825)	(-1.959)			(3.183)
Average			0.001245	-0.000522			0.001732
Annualized			32%	-14%			46%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Chile	0.072	0.732	0.744	0.670	0.104
(1,50,0.01)	Fraction>Chile	0.062	0.724	0.698	0.662	0.100
(1,150,0)	Fraction>Chile	0.176	0.710	0.566	0.684	0.256
(1,150,0.01)	Fraction>Chile	0.142	0.758	0.522	0.656	0.264
(5,150,0)	Fraction>Chile	0.112	0.742	0.740	0.694	0.122
(5,150,0.01)	Fraction>Chile	0.110	0.718	0.720	0.694	0.234
(1,200,0)	Fraction>Chile	0.158	0.760	0.518	0.684	0.266
(1,200,0.01)	Fraction>Chile	0.138	0.750	0.532	0.662	0.214

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Chile	0.108	0.744	0.666	0.676	0.152
	Mean	0.000808	0.015565	-0.000412	0.016614	0.001221
	Chile	0.001245	0.012134	-0.000522	0.012864	0.001732

Table IVa: Standard and Bootstrap test results for Trading Range Break - Philippines

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Cumulative average returns are reported for fixed 10-day periods after signals. Rules are identified as (short, long,band), where short represents the daily quote, long is the number of preceding days over which local maxima and mimima are calculated, and band is the percentage difference on the local maximum and minimum values needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals reported. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 10-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages across all 6 rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(1) - FIGARCH(1,δ,1) model. The rows reading fraction>Philip. refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Philippines" represents the actual mean return or standard deviation from the MSCI Philippines series.

Panel A: Standard Test Results for the Trading Range Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	81	76	0.024087 (3.372)	-0.020165 (-2.879)	0.7017	0.3684	0.044252 (4.460)
(1,50,0.01)	64	63	0.026355 (3.294)	-0.020402 (-2.656)	0.7031	0.4516	0.046757 (4.241)
(1,150,0)	50	40	0.018708 (2.052)	-0.025192 (-2.608)	0.6401	0.4449	0.043900 (3.332)
(1,150,0.01)	38	38	0.019887 (1.907)	-0.013057 (-1.344)	0.6579	0.4359	0.032993 (2.311)
(1,200,0)	41	35	0.020410 (2.035)	-0.033310 (-3.211)	0.6585	0.3333	0.053721 (3.758)
(1,200,0.01)	30	34	0.032035 (2.764)	-0.016850 (-1.627)	0.7667	0.1181	0.014888 (3.141)
Average			0.023580	-0.021496			0.045080
Annualized			62%	-56%			118%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Philip.	0.056	0.616	0.938	0.548	0.030
(1,50,0.01)	Fraction>Philip.	0.034	0.186	0.954	0.156	0.022
(1,150,0)	Fraction>Philip.	0.146	0.676	0.904	0.680	0.078
(1,150,0.01)	Fraction>Philip.	0.186	0.586	0.682	0.488	0.194
(1,200,0)	Fraction>Philip.	0.122	0.518	0.956	0.666	0.036
(1,200,0.01)	Fraction>Philip.	0.084	0.574	0.762	0.428	0.096

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Philip.	0.080	0.566	0.900	0.528	0.048
	Mean	0.007101	0.061423	-0.004910	0.075429	0.009580
	Philippines	0.023580	0.063940	-0.021496	0.068101	0.045080

Table IVb: Standard and Bootstrap test results for Trading Range Break - Taiwan

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Cumulative average returns are reported for fixed 10-day periods after signals. Rules are identified as (short, long,band), where short represents the daily quote, long is the number of preceding days over which local maxima and mimima are calculated, and band is the percentage difference on the local maximum and minimum values needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals reported. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 10-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages across all 6 rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(3) - FIGARCH(1,δ,0) model. The rows reading fraction>Taiwan refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Taiwan" represents the actual mean return or standard deviation from the MSCI Taiwan series.

Panel A: Standard Test Results for the Trading Range Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	83	77	0.020417 (2.232)	-0.011333 (-1.545)	0.5542	0.3766	0.031749 (2.690)
(1,50,0.01)	66	70	0.024933 (2.489)	-0.007499 (-1.049)	0.5818	0.4286	0.032492 (2.538)
(1,150,0)	48	40	0.010231 (0.765)	-0.023875 (-2.177)	0.5000	0.3902	0.034105 (2.135)
(1,150,0.01)	38	33	0.023163 (1.745)	-0.024946 (-2.061)	0.5263	0.4412	0.048109 (2.710)
(1,200,0)	41	33	0.000371 (-0.134)	-0.032320 (-2.626)	0.4634	0.3529	0.032691 (1.874)
(1,200,0.01)	31	29	0.009662 (0.574)	-0.028369 (-2.179)	0.5161	0.4333	0.038031 (1.973)
Average			0.014796	-0.021390			0.036243
Annualized			39%	-56%			95%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Taiwan	0.024	0.438	0.822	0.350	0.022
(1,50,0.01)	Fraction>Taiwan	0.014	0.470	0.644	0.148	0.050
(1,150,0)	Fraction>Taiwan	0.272	0.352	0.974	0.054	0.029
(1,150,0.01)	Fraction>Taiwan	0.042	0.296	0.944	0.026	0.014
(1,200,0)	Fraction>Taiwan	0.682	0.548	0.976	0.202	0.066
(1,200,0.01)	Fraction>Taiwan	0.374	0.634	0.940	0.026	0.088

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Taiwan	0.100	0.456	0.960	0.048	0.010
	Mean	0.005893	0.066692	-0.003481	0.068555	0.009374
	Taiwan	0.014796	0.065396	-0.021390	0.090499	0.036243

Table IVc: Standard and Bootstrap test results for Trading Range Break - Thailand

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Cumulative average returns are reported for fixed 10-day periods after signals. Rules are identified as (short, long,band), where short represents the daily quote, long is the number of preceding days over which local maxima and mimima are calculated, and band is the percentage difference on the local maximum and minimum values needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals reported. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 10-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages across all 6 rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(2) - FIGARCH(1,δ,0) model. The rows reading fraction>Thail. refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Thailand" represents the actual mean return or standard deviation from the MSCI Thailand series.

Panel A: Standard Test Results for the Trading Range Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	80	74	0.002870 (3.138)	-0.013848 (-1.391)	0.6750	0.4324	0.042549 (3.211)
(1,50,0.01)	67	59	0.026688 (2.678)	-0.015559 (-1.403)	0.6567	0.4576	0.042247 (2.880)
(1,150,0)	42	41	0.022814 (1.823)	-0.003151 (-0.211)	0.6224	0.4797	0.025965 (1.439)
(1,150,0.01)	35	32	0.020532 (1.502)	-0.333607 (-0.012)	0.7059	0.5312	0.021139 (1.052)
(1,200,0)	34	37	0.030915 (2.214)	-0.005111 (-0.345)	0.7272	0.4595	0.036026 (1.845)
(1,200,0.01)	29	29	0.025579 (1.698)	-0.003716 (-0.214)	0.7500	0.4828	0.029301 (1.358)
Average			0.025872	-0.006999			0.032971
Annualized			67%	-18%			86%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Thail.	0.020	0.842	0.688	0.178	0.030
(1,50,0.01)	Fraction>Thail.	0.060	0.836	0.636	0.320	0.092
(1,150,0)	Fraction>Thail.	0.060	0.832	0.262	0.094	0.194
(1,150,0.01)	Fraction>Thail.	0.158	0.810	0.158	0.166	0.402
(1,200,0)	Fraction>Thail.	0.052	0.926	0.354	0.108	0.100
(1,200,0.01)	Fraction>Thail.	0.130	0.790	0.292	0.188	0.270

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Thail.	0.054	0.866	0.372	0.164	0.124
	Mean	0.004154	0.084589	-0.010773	0.077403	0.014926
	Thailand	0.025872	0.055064	-0.006999	0.098898	0.032871

Table IVd: Standard and Bootstrap test results for Trading Range Break - Indonesia

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Cumulative average returns are reported for fixed 10-day periods after signals. Rules are identified as (short, long,band), where short represents the daily quote, long is the number of preceding days over which local maxima and mimima are calculated, and band is the percentage difference on the local maximum and minimum values needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals reported. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 10-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages across all 6 rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(2) - FIGARCH(1,δ,0) model. The rows reading fraction>Indon. refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Indonesia" represents the actual mean return or standard deviation from the MSCI Indonesia series.

Panel A: Standard Test Results for the Trading Range Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	85	81	0.033329 (3.118)	-0.022174 (-2.101)	0.6099	0.4493	0.055503 (3.722)
(1,50,0.01)	64	66	0.037590 (3.065)	-0.018787 (-1.616)	0.6667	0.3788	0.056377 (3.346)
(1,150,0)	42	40	0.046390 (3.081)	-0.026705 (-1.781)	0.6905	0.3500	0.073095 (3.445)
(1,150,0.01)	30	34	0.057509 (3.239)	-0.023011 (-1.420)	0.7586	0.3235	0.080520 (3.347)
(1,200,0)	33	35	0.055790 (3.294)	-0.024668 (-1.542)	0.7188	0.3714	0.080458 (3.453)
(1,200,0.01)	25	31	0.058385 (3.004)	-0.022992 (-1.355)	0.7500	0.3549	0.081378 (3.152)
Average			0.048166	-0.023056			0.071222
Annualized			126%	-60%			186%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Indon.	0.046	0.268	0.890	0.320	0.030
(1,50,0.01)	Fraction>Indon.	0.074	0.230	0.706	0.248	0.076
(1,150,0)	Fraction>Indon.	0.044	0.396	0.906	0.142	0.038
(1,150,0.01)	Fraction>Indon.	0.030	0.123	0.834	0.114	0.028
(1,200,0)	Fraction>Indon.	0.034	0.524	0.864	0.132	0.042
(1,200,0.01)	Fraction>Indon.	0.056	0.192	0.742	0.128	0.064

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Indon.	0.028	0.282	0.890	0.152	0.022
	Mean	0.007879	0.116019	-0.010695	0.104738	0.018574
	Indonesia	0.048166	0.124138	-0.023056	0.140213	0.071222

Table IVe: Standard and Bootstrap test results for Trading Range Break - Mexico

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Cumulative average returns are reported for fixed 10-day periods after signals. Rules are identified as (short, long,band), where short represents the daily quote, long is the number of preceding days over which local maxima and mimima are calculated, and band is the percentage difference on the local maximum and minimum values needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals reported. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 10-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages across all 6 rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(1) - FIGARCH(1,δ,0) model. The rows reading fraction>Mexico refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Mexico" represents the actual mean return or standard deviation from the MSCI Mexico series.

Panel A: Standard Test Results for the Trading Range Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	108	56	0.021249 (2.029)	-0.006497 (-1.533)	0.7037	0.5091	0.027746 (2.456)
(1,50,0.01)	87	50	0.022318 (1.970)	-0.004780 (-0.293)	0.7126	0.6200	0.017538 (1.441)
(1,150,0)	68	16	0.021731 (1.676)	-0.008018 (-0.922)	0.6618	0.4375	0.029749 (1.561)
(1,150,0.01)	57	15	0.022021 (1.568)	-0.006526 (-0.800)	0.7018	0.5333	0.028547 (1.434)
(1,200,0)	66	12	0.019127 (1.346)	-0.010753 (-0.929)	0.6364	0.5385	0.029880 (1.388)
(1,200,0.01)	55	12	0.022722 (1.616)	-0.000083 (-0.391)	0.7308	0.5833	0.022805 (1.043)
Average			0.021528	-0.004516			0.026044
Annualized			56%	-12%			68%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Mexico	0.134	0.916	0.756	0.172	0.144
(1,50,0.01)	Fraction>Mexico	0.114	0.964	0.354	0.250	0.416
(1,150,0)	Fraction>Mexico	0.112	0.586	0.718	0.068	0.158
(1,150,0.01)	Fraction>Mexico	0.116	0.836	0.618	0.060	0.240
(1,200,0)	Fraction>Mexico	0.208	0.596	0.710	0.084	0.230
(1,200,0.01)	Fraction>Mexico	0.086	0.856	0.512	0.064	0.328

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Mexico	0.100	0.932	0.688	0.046	0.148
	Mean	0.013379	0.065785	-0.000261	0.084595	0.013640
	Mexico	0.021528	0.051966	-0.004516	0.130698	0.026044

Table IVf:: Standard and Bootstrap test results for Trading Range Break - Brazil

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Cumulative average returns are reported for fixed 10-day periods after signals. Rules are identified as (short, long,band), where short represents the daily quote, long is the number of preceding days over which local maxima and mimima are calculated, and band is the percentage difference on the local maximum and minimum values needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals reported. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 10-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages across all 6 rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(1) - FIGARCH(1,δ,1) model. The rows reading fraction>Brazil refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Brazil" represents the actual mean return or standard deviation from the MSCI Brazil series.

Panel A: Standard Test Results for the Trading Range Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	93	54	0.013824 (0.809)	-0.038677 (-2.918)	0.5699	0.4259	0.052500 (2.834)
(1,50,0.01)	78	52	0.013983 (0.755)	-0.025667 (-2.004)	0.5128	0.5000	0.039648 (2.045)
(1,150,0)	53	24	0.008682 (0.271)	-0.023416 (-1.265)	0.5472	0.5103	0.032099 (1.205)
(1,150,0.01)	40	21	0.010232 (0.325)	-0.016469 (-0.890)	0.5250	0.6818	0.026701 (0.900)
(1,200,0)	46	20	0.016678 (0.750)	-0.006310 (-0.453)	0.6087	0.6667	0.023039 (0.793)
(1,200,0.01)	35	17	0.020514 (0.864)	0.007152 (0.096)	0.5714	0.7222	0.013362 (0.417)
Average			0.013985	-0.017231			0.031225
Annualized			36%	-45%			81%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Brazil	0.380	0.436	0.948	0.266	0.054
(1,50,0.01)	Fraction>Brazil	0.408	0.396	0.850	0.264	0.162
(1,150,0)	Fraction>Brazil	0.540	0.378	0.792	0.258	0.242
(1,150,0.01)	Fraction>Brazil	0.510	0.270	0.672	0.212	0.354
(1,200,0)	Fraction>Brazil	0.254	0.364	0.552	0.470	0.362
(1,200,0.01)	Fraction>Brazil	0.208	0.296	0.350	0.364	0.538

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Brazil	0.316	0.390	0.742	0.322	0.226
	Mean	0.009910	0.109982	-0.008931	0.164105	0.018840
	Brazil	0.013985	0.103658	-0.017231	0.160767	0.031225

Table IVg: Standard and Bootstrap test results for Trading Range Break - Argentina

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Cumulative average returns are reported for fixed 10-day periods after signals. Rules are identified as (short, long,band), where short represents the daily quote, long is the number of preceding days over which local maxima and mimima are calculated, and band is the percentage difference on the local maximum and minimum values needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals reported. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 10-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages across all 6 rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(3) - FIGARCH(1,δ,1) model. The rows reading fraction>Argent. refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Argentina" represents the actual mean return or standard deviation from the MSCI Argentina series.

Panel A: Standard Test Results for the Trading Range Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	90	59	-0.001666 (-0.391)	-0.020999 (-1.622)	0.5778	0.4138	0.019332 (1.021)
(1,50,0.01)	69	53	-0.002757 (-0.423)	-0.013389 (-1.052)	0.5217	0.4206	0.010632 (0.515)
(1,150,0)	51	37	0.022145 (1.222)	0.004708 (0.072)	0.5577	0.4722	0.017435 (0.627)
(1,150,0.01)	38	33	0.024947 (1.189)	-0.001885 (-0.249)	0.5600	0.4710	0.026832 (0.998)
(1,200,0)	41	30	0.027459 (1.376)	0.000781 (0.226)	0.5854	0.5333	0.019646 (0.724)
(1,200,0.01)	29	28	0.045509 (2.016)	0.001728 (-0.064)	0.5517	0.5556	0.043781 (1.449)
Average			0.019273	-0.003640			0.022860
Annualized			50%	-10%			60%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Argent.	0.596	0.294	0.706	0.906	0.378
(1,50,0.01)	Fraction>Argent.	0.636	0.386	0.538	0.876	0.564
(1,150,0)	Fraction>Argent.	0.156	0.486	0.246	0.670	0.454
(1,150,0.01)	Fraction>Argent.	0.150	0.396	0.364	0.772	0.368
(1,200,0)	Fraction>Argent.	0.156	0.484	0.250	0.674	0.452
(1,200,0.01)	Fraction>Argent.	0.068	0.356	0.364	0.744	0.266

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Argent.	0.160	0.400	0.380	0.780	0.378
	Mean	0.000734	0.177308	-0.016588	0.218167	0.017330
	Argentina	0.019273	0.149866	-0.003640	0.115479	0.022860

Table IVh: Standard and Bootstrap test results for Trading Range Break - Chile

Panel A reports standard test results for daily data from 1 January 1988 to 14 May 2002. Cumulative average returns are reported for fixed 10-day periods after signals. Rules are identified as (short, long,band), where short represents the daily quote, long is the number of preceding days over which local maxima and mimima are calculated, and band is the percentage difference on the local maximum and minimum values needed to generate a signal. "N(buy)" and "N(sell)" refer to the number of buy and sell signals reported. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and sell return from the unconditional 10-day mean, and buy-sell from zero. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The last two rows of panel A report averages and annualized averages across all 6 rules. In Panel B we present the bootstrap test results for each rule and the simulated AR(2) - FIGARCH(1,δ,0) model. The rows reading fraction>Chile refer to the fraction of simulations generating a mean or standard deviation larger than those from the actual series. Panel C displays results for the averages across all rules for each reported statistic. "Mean" refers to the average return or standard deviation from the 1000 simulated series, while "Chile" represents the actual mean return or standard deviation from the MSCI Chile series.

Panel A: Standard Test Results for the Trading Range Rules

RULE	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1,50,0)	88	74	0.018582 (2.582))	-0.010591 (-2.505)	0.6818	0.3562	0.029174 (3.629)
(1,50,0.01)	70	48	0.015274 (1.768)	-0.015810 (-2.730)	0.6571	0.3830	0.031084 (3.255)
(1,150,0)	54	32	0.015516 (1.592)	-0.014742 (-2.115)	0.6111	0.3333	0.030258 (2.661)
(1,150,0.01)	42	19	0.016630 (1.547)	-0.025042 (-2.511)	0.6667	0.3000	0.041672 (2.957)
(1,200,0)	43	25	0.020793 (2.098)	-0.010069 (-1.414)	0.6279	0.3846	0.030861 (2.190)
(1,200,0.01)	36	13	0.021478 (2.002)	-0.045467 (-3.521)	0.6667	0.2485	0.066945 (4.060)
Average			0.018046	-0.020287			0.038332
Annualized			47%	-53%			100%

Panel B: Bootstrap test results, Individual Rules

RULES	Simulated p-value	Buy	Buy std.	Sell	Sell std.	Buy-Sell
(1,50,0)	Fraction>Chile	0.064	0.718	0.852	0.698	0.046
(1,50,0.01)	Fraction>Chile	0.208	0.742	0.872	0.806	0.100
(1,150,0)	Fraction>Chile	0.132	0.470	0.886	0.394	0.070
(1,150,0.01)	Fraction>Chile	0.184	0.622	0.940	0.384	0.058
(1,200,0)	Fraction>Chile	0.076	0.700	0.694	0.252	0.088
(1,200,0.01)	Fraction>Chile	0.131	0.838	0.976	0.308	0.020

Panel C: Bootstrap test results, Rule Averages

Rule Average	Fraction>Chile	0.026	0.346	0.978	0.158	0.010
	Mean	0.006968	0.066728	-0.002360	0.071053	0.009325
	Chile	0.018046	0.049983	-0.020287	0.074713	0.038332

TABLE V: Unconditional Moments of Simulated Series								
	Simulations							
Country	Returns				Standard Deviation			
	Mean	Var.	Skew.	Kurt.	Mean	Var.	Skew.	Kurt.
Philip.	0.000120	0.000669	0.543942	21.917222	0.000427	0.001667	1.025291	20.531606
Taiwan	0.000196	0.000383	0.039717	3.376746	0.000371	0.000202	0.173094	1.850267
Thail.	-0.000318	0.000452	0.205223	11.059400	0.000419	0.000539	0.623053	13.057513
Indon.	-0.000234	0.000937	0.368463	32.188810	0.000552	0.002974	1.397866	30.615820
Mexico	0.000938	0.000404	-0.282100	9.625091	0.000434	0.000639	0.514482	9.370741
Brazil	0.000367	0.001979	-0.597741	12.952611	0.001015	0.006869	0.756778	11.027701
Argent.	-0.000568	0.005880	-0.291576	22.219297	0.001419	0.020743	0.882996	18.516635
Chile	0.000237	0.000330	-0.231457	13.516912	0.000356	0.000866	0.750030	12.301535