Structural Breaks, Long Memory, or Unit Roots in Stock Prices: Evidence from Emerging Markets

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ABSTRACT

This paper investigates whether daily stock price indices from fourteen emerging markets are random walk (unit root) or mean reverting long memory processes. We use an efficient statistical framework that tests for random walks in the presence of multiple structural breaks at unknown dates. This approach allows us to investigate a broader range of persistence than that allowed by the I(0)/I(1) paradigm about the order of integration, which is usually implemented for testing the random walk hypothesis in stock market indices. Our approach extends Robinson's (1994) efficient test of unit root against fractional integration to allow for multiple endogenously determined structural breaks. For almost all countries, we find support for the random walk hypothesis, with the exception of four stock markets, where weak evidence of mean reverting long memory exist. Structural breaks have impact on the unit root behavior only for Mexico; for all other 11 markets unit roots exist even when structural breaks are not taken into account. In order to check the robustness of our results, we use the two-step feasible exact local Whittle (FELW2ST) estimator of Shimotsu (2010), which allows for polynomial trends, non-normal distributions, and non-stationarity. The results from the semi-parametric FELW2ST approach shows that, except for Mexico, stock price indices of 13 emerging markets are not mean reverting.

Key words: *Emerging Markets, Random Walk, Structural Breaks, Market Liberalization*
JEL Classifications: G15; G14; C22

1. INTRODUCTION

During the last two decades, the Efficient Market Hypothesis (EMH), originally attributed to Fama (1965), is a central debate in the financial literature because of its important implications. In an efficient market, prices always reflect all available information. Fama (1970) defines three forms of the EMH, weak, semi-strong, and strong, based on different degrees of information. In the weak form of market efficiency, stock prices reflect all the information available from past prices or returns. In the semi-strong form, prices of financial assets instantly reflect publicly available information. Finally, strong-form market efficiency

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Esin Cakan gratefully acknowledges the financial support from the Summer Research Grant Fund of University of New Haven. The views expressed in this paper are those of the authors and do not necessarily reflect those of the University of New Haven Summer Research Grant Members. We thank an anonymous referee and the editor of the International Econometric Review for helpful comments that certainly improved the analysis in the paper. All errors remain our responsibility.

holds even when prices on financial assets reflect inside information. The three forms of market efficiency determine the information needed to test the relevant hypothesis. When a stock market is weakly efficient, for example, participants cannot consistently use past prices to predict future prices. When markets are efficient, price fluctuations must be a response to new information. Since information flow is random, share prices must also change unpredictably. When stock prices are random walk, past information does not predict future prices and the weak form of EMF holds. When stock prices are not random walk and mean revering, past information can help forecast the market. The failure to reject the random walk leads us to conclude that the weak form of the Efficient Market Hypothesis is supportable for the daily stock prices of emerging market economies. This study contributes to the literature by applying methodological innovation as well as through our findings against the mean reversion in the context of emerging stock markets.

Country	**Market liberalization date**	**Liberalization status**
Argentina	October 1991	Fully open
Brazil	May 1991	49% of voting common stock and 100% of non-voting participating, preferred stock.
China	February 1992	Limited under QFII and QDII. B-shares traded on February 21, 1992 open foreigners
Hong Kong	--	Large interest from overseas investors in September 1986 upon full membership to FIBV
Hungary	January 1996	Most stocks available to foreigners
South Korea	January 1992	20% on October 1, 1996
Malaysia	December 1988	100% available to foreign investors
Mexico	May 1989	30% of total capital[a]
Philippines	October 1989	Investable up to 40%
Russia	July 1996	Fully open
Taiwan	January 1991	Investable up to 30% on November 1, 1996
Thailand	December 1988	25% for bank stocks and 49% for others
Turkey	August 1989	100% open

Table 1.1 Market liberalization dates of emerging markets.
Notes: This table reports market liberalization dates for the fourteen emerging stock markets under investigation in this study. This information is obtained from IFC (1997) and several other sources.
[a] Certain classes may be freely available to foreign investors.

Shocks from financial market liberalization, other structural changes due to financial crises, or other influential economic changes may affect equity price of emerging markets, which is the main motivation of our study. Our sample period covers daily data until August 12, 2014 for all series, but the starting dates differ across countries as shown in Table 1.2. These sample periods include more than one known structural breaks for each country. All countries in our sample liberalized their financial markets to various degrees during the sampling period (see Table 1.1), except Hong Kong, which had some degree of liberalization from the early periods covered. Additionally, each of the countries experienced one or more financial crises, severe recession, or major events like wars. For example, the deepest recessions of the last few decades affecting some countries in our sample occurred during 1982-1983, the first Gulf war in 1990-91, the Asian financial crises in 1997-98, the Russian financial crises in 1998, the 9/11 terrorist attack in 2001, the second Gulf war in 2003, and the global recession of 2007-09, among other country specific cases. Any of these events may create structural breaks, shifts in the mean and trend or both, in stock market prices. Thus, the objective of this study is to examine the effect of financial liberalization and structural breaks on stock prices and to test the validity of an efficient market hypothesis. We investigate whether stock price indices of fourteen emerging markets, namely Argentina, Brazil, China, Hong Kong, Hungary, South Korea, Malaysia, Mexico, Philippines, Poland, Russia, Taiwan, Thailand, and Turkey are

Country	Emerging Market Stock Exchange Index	Beginning of the Index	Number of Breaks	Break dates
Argentina	Merval	Oct 19, 1989	5	Aug 9, 1991; Feb 2, 2001; Dec 20, 2002; Sep 26, 2008; Aug 5, 2011
Brazil	Bovespa	Apr 12, 1983	7	Mar 21, 1986; Dec 25, 1987; Mar 15, 1990; Oct 24, 1997; Jun 19, 2002; Sep 26, 2008; Apr 21, 2010
China	Shanghai SE Composite	Jan 2, 1991	5	May 20, 1992; Jan 13, 1994; Jul 27, 2001; Jan 30, 2006; Feb 22, 2008
Hong Kong	Hang Seng	Dec 30, 1964	7	Nov 17, 1967; Oct 30, 1972; Apr 23, 1975; Aug 9, 1982; Oct 21, 1997; Aug 6, 2001; Sep 2, 2008
Hungary	Budapest (BUX)	Jan 2, 1991	7	Aug 31, 1993; Jan 30, 1996; Aug 10, 1998; Feb 20, 2001; Nov 4, 2004; Oct 8, 2008; Jan 20, 2010
South Korea	Korea SE Composite (KOSPI)	Dec 31, 1974	7	Jan 4, 1979; Aug 5, 1985; May 11, 1989; Nov 12, 1993; Nov 21, 1997; Sep 6, 2000; Aug 12, 2008
Malaysia	Kuala Lumpur SE Composite	Jan 2, 1980	7	Sep 23, 1981; Jun 16, 1983; Jan 24, 1986; Oct 19, 1987; Feb 17, 1997; Nov 23, 1998; Aug 24, 2000
Mexico	IPC (BOLSA)	Jan 4, 1988	5	May 17, 1991; Dec 21, 1994; Jul 22, 2002; Oct 1, 2008; Apr 26, 2010
Philippines	Philippines SE Composite	Jan 2, 1986	6	Sep 11, 1987; Aug 9, 1990; Dec 6, 1993; Aug 14, 1997; Oct 14, 2002; Jun 9, 2008
Poland	Warsaw General Index	Apr 16, 1991	6	Jan 6, 1993; Mar 30, 1994; Jan 25, 1996; Jul 19, 2002; Mar 3, 2008; May 1, 2009
Russia	RTS Index	Sep 1, 1995	5	Aug 1, 1997; Aug 19, 1998; Sep 15, 2000; Sep 8, 2008; Aug 3, 2011
Taiwan	Taiwan SE Weighted	Dec 31, 1984	7	Jan 9, 1987; Oct 10, 1988; May 17, 1990; Dec 13, 1993; Oct 13, 2000; Sep 10, 2008; Aug 4, 2011
Thailand	Bangkok SET	Apr 30, 1975	7	Aug 1, 1977; Aug 29, 1986; Sep 12, 1990; Apr 10, 1996; Oct 8, 1998; Jun 11, 2003; Aug 29, 2008
Turkey	ISE National100	Jan 4, 1988	7	May 2, 1989; Aug 30, 1990; Feb 10, 1993; Dec 10, 1999; Sep 12, 2001; Oct 4, 2007; May 18, 2009

Table 1.2 Emerging Market Stock Exchange Indices definitions, beginning of indices and break dates of the series.
Notes: This table reports the beginning of the stock indices of each emerging countries and break dates of each series estimated from Bai and Perron (1998) given in Eqs. (3.1) and (3.2). The break dates are endogenously estimated from the data. Data is obtained from Thomson Reuters Datastream database.

random walk or mean reverting processes. In other words, we test the validity of an efficient market hypothesis in emerging markets for daily stock returns by employing statistics that test the unit root hypothesis against fractional or long memory alternatives. Diebold and Rudebush (1991), Hassler and Wolters (1994), and Lee and Schmidt (1996) show that most of unit root tests have very low power if the underlying process is fractionally integrated. Unlike other studies, we test for a unit root against fractional unit roots. When the underlying series is not a random walk, testing the I(1) hypothesis against the stationarity hypothesis I(0) results in very low power. We use a test developed by Robinson (1994), which outperforms rival methods and allows for fractional or long memory alternatives. In a long memory model, shocks have a long lasting effect, but the underlying process is mean reverting, including possible structural breaks. Further, long memory is not only the property of non-stationary processes; stationary processes may have long memory as well. Long memory can be captured by a fractionally integrated I(d) model, where the fractional order of integration d is a real positive number.

We find that the structural breaks affect the long memory properties of the emerging market stock indices. The estimated values of fractional integration order d are all smaller when accounting for structural breaks as compared to allowing for only a linear trend. However, the range of non-integer d values that can not be rejected cover the unit root case $d = 1$ for 10 of the 14 emerging stock markets we examine, implying that the series does not present evidence of mean reverting behavior.

We discover evidence of mean reversion only for Argentina, Brazil, South Korea, and Mexico. For Mexico, however, structural breaks accounts for a unit root, where as unit roots exists for Argentina, Brazil, and South Korea even when structural breaks are not allowed. However, even for those four countries, the upper limit of the d estimates closely borders the unit root. In order to check the robustness of the results, we estimate the orders of integration using the two-step feasible exact local Whittle (FELW2ST) estimator of Shimotsu (2010), which allows for polynomial trends, non-normal distributions, and non-stationarity. The evidence from the semi-parametric FELW2ST approach indicates that, except for Mexico, stock price indices of 13 emerging markets are not mean reverting, even after considering the effect of endogenously determined structural breaks, which complements the results of Robinson's (1994) parametric testing. The results we obtain are, thus, robust to the specification of the short memory component in Robinson's (1994) efficient testing approach.

The organization of the paper is as follows. Section 2 discusses structural breaks in stock markets. Section 3 presents empirical methodology. Section 4 describes the data and makes preliminary analyses. Section 5 presents the estimation results. Section 6 offers the conclusions.

2. STRUCTURAL BREAKS AND STOCK MARKET LIBERALIZATION

Several studies consider structural breaks and market liberalization in equity markets (Bekaert et al., 2002a, 2002b; Henry, 2000; Bekaert and Harvey, 2000; Kawakatsu and Morey, 1999; Stulz and Wasserfallen, 1995; Errunza et al., 1992; Chaudhuri and Wu, 2003). However, no studies to date test the random walk hypothesis against the alternative of mean reversion of in equity prices in the presence of multiple structural breaks. We do so by estimating the score test by Robinson (1994), taking into account the effect of multiple level and trend breaks. Our methodology estimates multiple structural breaks endogenously from the data using the method in Bai and Perron (1998). Estimated structural break dates are consistent with the corresponding market liberalization and financial crises dates, implying that structural breaks correspond to real economic events and not to statistical artifacts. For the stock prices in emerging markets, the literature is thorough on testing unit roots, but only a few recent studies deal with structural breaks, even fewer deal with long memory models, and none deal with long memory and structural breaks together. Errunza et al. (1992), Stulz and Wasserfallen (1995), Kawakatsu and Morey (1999), Henry (2000), Bekaert and Harvey (2000), Bekaert et al. (2002a, 2002b), and Ozdemir (2008) study stock market prices for random walk behavior and consider the impact of structural breaks in emerging equity markets. Chaudhuri and Wu (2003) investigate whether stock price indices of seventeen emerging markets are random walk, I(1), or mean reversion processes, I(0). Using Zivot and Andrews's (1992) test that accounts for one structural break in the series, they note that, for fourteen countries, stock prices exhibit structural breaks and reject the null hypothesis of a random walk at the 1% and 5% significance level, implying that the weak form the EMH does not hold for those countries. The studies testing the EMH in stock price indices by testing unit for the presence of unit root allow for one structural break, determined exogenously (Perron, 1989) or endogenously (Zivot and Andrews, 1992), and assume the effect of market liberalization. The market liberalization dates and status of emerging equity markets studied in this paper are in Table 1.1.

3. EMPIRICAL METHODOLOGY

Robinson (1994) developed a general procedure for testing unit roots as well as other non-stationary alternatives. Unlike the other unit root tests (Dickey and Fuller, 1979; Phillips and Perron, 1998; and others), which test for autoregressive (AR) unit roots, i.e., integer order of integration, Robinson's procedure offers a fractional order of integration in addition to other appealing hypotheses. This section provides a brief account of the approach we use to test fractional integration in the presence of structural breaks at unknown dates.

We extend beyond previous studies determining the order of integration in fractionally integrated models by accounting for multiple endogenously determined structural breaks. Gil-Alana (2003) assumes the structural break dates are known and uses dummy variable to incorporate the breaks. Gil-Alana (2008) employs a procedure based on minimizing the residuals sum squared where a single structural break is allowed at an unknown date. We extend this procedure to the case of multiple structural breaks at unknown dates. For this, we use the procedure of Gil-Alana (2008) and the principles suggested in Bai and Perron (1998). Additionally, Gil-Alana (2008) estimates different fractional orders in two regimes and does not construct statistical tests about the order of integration, while we construct confidence interval for a single fractional order in all regimes and also construct statistical tests about the order of integration. Specifically, our procedure allows multiple structural breaks in the form of level and trend shifts at endogenously determined dates and uses the Robinson (1994) LM test to determine the fractional order of integration. Since we use a grid of finite fractional integration orders as suggested in Robinson (1994), our method may lead to inconsistent estimates of break dates and fractional integration if the true fractional order is not in the finite set. Nevertheless, all previous studies using this approach face the same limitation.

Consider the multiple regression of the form:

$$y_t = \beta' z_t + x_t, t = 1,2,...,T \tag{3.1}$$

where y_t is the time series of stock index we observe, β is a $k \times 1$ vector of unknown parameters, and z_t is a $k \times 1$ vector of observable variables, which could include a constant, polynomials in time trend (t), and structural break dummies, as we would assume in the application section of this paper. The presence of such deterministic regressors does not affect the limiting null and local distributions of the Robinson test statistic, which is an advantage over other unit root tests. T is the sample size.

We consider a general case, where zt includes a constant, a linear time trend, and $m = 2k$ level, and trend shift dummies $DLT_{t,i}^{\tau l} = (DL_{t,i}^{\tau l}, DT_{t,i}^{\tau l})'$ at the dates $i = T_{b,1}^{\tau l}, T_{b,2}^{\tau l},..., T_{b,k}^{\tau l}$. Here $DL_{t,i}^{\tau l} = 1$ if $t > T_{b,i}^{\tau l}$ and zero otherwise, $DT_{t,i}^{\tau l} = t - T_{b,i}^{\tau l}$ if $t > T_{b,i}^{\tau l}$ and zero otherwise. For brevity, we define T_k as the set of disjoint break dates $T_b = \{T_{b,1}^{\tau l},..., T_{b,k}^{\tau l}\}$. We define $\beta' z_t$ as follows:

$$\beta' z_t = \mu + \delta t + \sum_{i=1}^{k} (\varphi_i DL_{t,i}^{\pi} + \theta_i DT_{t,i}^{\pi})$$

The regression errors x_t are:

$$(1-L)^d x_t = u_t \tag{3.2}$$

where, L is the lag operator, u_t is integrated of order zero, I(0), covariance stationary process with spectral density function that is positive and finite at zero frequency. The order of integration d is not restricted to integer values and can assume any value on the real line.

The basis for the idea behind this model with structural breaks is on the least square principle proposed by Bai and Perron (1998). First, a grid of values $d_0 = 0.00, 0.01, \ldots, 1.20$ is chosen for d. Following the procedure for each k-partition $\{T_1,...,T_k\}$, denoted $\{T_k\}$, the least squares estimates of μ, δ, ϕ_i, and θ_i, $i = 1,...,k$, are obtained by minimizing the sum of squared residuals in the d_0-differenced models, that is, the residuals sum of squares (RSS):

$$\sum_{t=1}^{T} (1-L)^{d_0} \left(y_t - \mu - \delta t - \sum_{i=1}^{k} [\varphi_i DL_{t,i}^{\pi} + \theta_i DT_{t,i}^{\pi}] \right)^2$$

is minimized over all values of $\{T_1,...,T_k\}$, yielding estimates $\hat{\mu}$, $\hat{\delta}$, $\hat{\phi}_i$, and $\hat{\theta}_i$, $i = 1,...,k$, and break dates $\{\hat{T}_k\}$. The above procedure requires prior determination of the number of breaks k. We employ Schwarz's (1978) Bayesian information criterion (BIC) to select the number of breaks. Accordingly, the number of breaks, k, is selected to minimize the criterion $\text{BIC}(k) = \ln[\text{RSS}(\hat{T}_k)/(T - n)] + 2n\ln(T) / T$. The fractional order of differencing d is determined by calculating the test statistics of Robinson (1994) for each value of d_0 in the grid. The outline for this procedure is below.

In order to test the null hypothesis:

$$H_0 : d = d_0 \tag{3.3}$$

Robinson (1994) developed the following score test statistic:

$$\hat{r} = \left(\frac{\sqrt{T}}{\hat{\sigma}^2} \right) \sqrt{\hat{A}}\hat{a} \tag{3.4}$$

where

$$\hat{a} = -\frac{2\pi}{T} \sum_{j=1}^{T-1} \psi(\lambda_j) g(\lambda_j;\eta) I(\lambda_j), \; I(\lambda_j) = \frac{1}{2\pi T} \left| \sum_{t=1}^{T} \hat{u}_t e^{i\lambda_j t} \right|, \; \lambda_j = \frac{2\pi j}{T}, \; \hat{\sigma}^2 = \frac{2\pi}{T} \sum_{j=1}^{T-1} g(\lambda_j;\hat{\eta}) I(\lambda_j)$$

$$\hat{A} = \frac{2}{T} \left(\sum_{j=1}^{T-1} \psi(\lambda_j)\psi(\lambda_j)' - \sum_{j=1}^{T-1} \psi(\lambda_j)\hat{\xi}(\lambda_j)' \times \left(\sum_{j=1}^{T-1} \hat{\xi}(\lambda_j)\hat{\xi}(\lambda_j)' \right)^{-1} \times \sum_{j=1}^{T-1} \hat{\xi}(\lambda_j)\psi(\lambda_j)' \right) \tag{3.5}$$

$$\hat{\xi}(\lambda_j) = \frac{\partial}{\partial \eta} \log g(\lambda_j;\hat{\eta}), \qquad \psi(\lambda_j) = \text{Re}\left\{ \frac{\partial}{\partial \gamma} \log \varphi(e^{-i\lambda_j};\gamma_0) \right\}$$

and $I(\lambda_j)$ is the periodogram of $\hat{u}_t$. The parameter estimates $\hat{\eta}$ derive from the Whittle Maximum Likelihood (WML) method, obtained by:

$$\hat{\eta} = \arg\min_{\eta \in \Lambda} \frac{2\pi}{T} \sum_{j=1}^{T-1} g(\lambda_j;\eta) I(\lambda_j) \tag{3.6}$$

where $g(\lambda_j;\eta)$ is the known function of the parametric spectral density of u_t, which is defined below.

The model in equation (3.2) is completed by specifying a particular parametric form for the process u_t. We will adopt a fairly general specification for u_t and assume that it is nested within an AutoRegressive Moving Average (ARMA) model. When u_t is a general ARMA process, then x_t becomes an autoregressive fractionally integrated moving average (ARFIMA) process, which is one of the most commonly used parametric specification for long memory, introduced by Granger and Joyeux (1980) and Hosking (1981). The ARMA model with autoregressive order p and moving average order q is denoted as ARMA(p,q) and denoted as:

$$\phi(L)u_t = \psi(L)\varepsilon_t \tag{3.7}$$

which implies the ARFIMA(p,d,q) model for x_t is given by:

$$\phi(L)(1-L)^d x_t = \psi(L)\varepsilon_t \tag{3.8}$$

where ε_t is white noise with variance σ^2, and $\phi(L) = 1 - \Sigma_{j=1}^{p}\phi_j L^j$ and $\psi(L) = 1 - \Sigma_{j=1}^{q}\psi_j L^j$ are polynomials in the lag operator L with degrees p and q, respectively. We assume that $\phi(Z)$ and $\psi(Z)$ share no common roots and $\phi(Z) \neq 0$, $\psi(Z) \neq 0$ for $Z \leq 1$. The parametric spectral density functions of the ARMA and ARFIMA models in (3.7) and (3.8) are given, respectively, by:

$$f(\lambda;\sigma^2,\eta) = \frac{\sigma^2}{2\pi}\left|\frac{\psi(e^{-i\lambda})}{\phi(e^{-i\lambda})}\right|, \; -\pi < \lambda \leq \pi \tag{3.9}$$

and

$$f(\lambda;\sigma^2,\eta) = \frac{\sigma^2}{2\pi}\left|\frac{\psi(e^{-i\lambda})}{\phi(e^{-i\lambda})}\right|^2 \left|1-e^{-i\lambda}\right|^{-2d}, \; -\pi < \lambda \leq \pi \tag{3.10}$$

where η is a $l \times 1$ vector of unknown parameters.

For the ARMA model in (3.7) $\eta = (\phi_1,...,\phi_p,\psi_1,...,\psi_q)'$ with $l = p + q$ and for the ARFIMA model in (3.8) $\eta = (d,\phi_1,...,\phi_p,\psi_1,...,\psi_q)'$ with $l = p + q + 1$, implying $g(\lambda_j;\eta) = |\psi(e^{-i\lambda_j})/\phi(e^{-i\lambda_j})|$. In the fractional integration testing approach we use, d is fixed under the null hypothesis and need not be estimated, thus (3.9) rather than (3.10) is relevant for the empirical application in this paper. On the assumption that the order (p,q) of the ARMA or ARFIMA model is known a priori, the model parameters η are estimated by the maximum likelihood methods.

To summarize our procedure is implemented as follows:

1. We select a value d_0 (the value of the fractional integration order d under the null hypothesis) in the grid $\{d_0^1 + i\Delta_d\}$, where $i = 1,...,s$, and Δ_d is the grid increment.
2. Given d_0, an initial disjoint break date T_1 is selected and the residuals $\hat{u}_t = (1 - L)^{d_0}$, $\hat{x}_t = (1 - L)^{d_0} y_t - \hat{\beta}'[(1 - L)^{d_0} z_t]$ are obtained
3. Given $\hat{u}_t$, test statistic $\hat{r}$ is calculated from equation (3.4).
4. Break dates are updated using the Bai and Perron (1998) algorithm.
5. Steps 2 - 4 is repeated until $\Sigma_{t=1}^{T}\hat{u}_t^2$ is minimized.
6. Steps 1 - 5 is repeated until $i = s$.

At each step of minimization of RSS($\hat{T}_k$) for given d_0, the parameters $\hat{\beta}$ and the nuisance parameters $\hat{\eta}$ are estimated sequentially as described above.

Under certain regularity conditions and the null hypothesis given above, Robinson (1994) shows that $\hat{r}$ approaches a normal distribution with zero mean and variance one as T approaches infinity. An approximate one sided test of H_0: $d = d_0$ is rejected in favor of H_0: $d > d_0$ ($d < d_0$) at the 100α% level, when $\hat{r} > z_\alpha$ ($r < -z_\alpha$), and where α is the probability that a standard normal variate exceeds z_α. This and other versions of the Robinson (1994) test are used in empirical applications by Gil Alana and Robinson (1997) and Gil Alana (1999, 2000, 2001, 2002), among many others.

4. DATA AND PRELIMINARY ANALYSIS

Our study examines the daily US dollar value of the stock price index of fourteen emerging market countries namely, Argentina, Brazil, China, Hong Kong, Hungary, South Korea, Malaysia, Mexico, Philippines, Poland, Russia, Taiwan, Thailand, and Turkey. We obtained stock price indices from the Thomson Reuters Datastream database. The stock exchanges of each country begin operation at different dates; therefore, the data span is different for each country. Table 1.2 presents the emerging markets included in the sample, the local names of the price indices, and the beginning date of the index used in our study. The sample ends in August 12, 2014 for all series, but the starting date is different for each market as shown in Table 1.2.

Figure 4.1 Time series plots of logarithm of stock price indices and fitted trends with structural breaks.

(continued on the next page)

Notes: Figures plot he logarithm of the stock market indices (solid line) and the fitted trend lines (dashed line) with structural break dummies included. Number of breaks and break dates are specified as given in Table 1.2.

Figure 4.1 displays plots of each logarithm of stock price indices, which have a non-stationary appearance. The time series plots of these market indices help visualize the existence of possible structural breaks in these markets. As indicated by the plots in Figure 4.1, the indices in general show large fluctuations over time, and there seem some apparent break points that generally correspond to changes in growth rates over long intervals. For example, for Argentina, the equity index level jumped in the mid 1990s, the slope of the trend line declined in the late 1990s, the index jumped again in the early 2000s with a positive sloped trend line, with a final trend break in 2007. For Korea, two level and trend shifts in the late 1980s and the late 1990s are noteworthy. In China, a break apparently occurs in both the level and the slope of the trend line around 1993 with three breaks in the trend around 2001, 2006, and 2007. A pervasive examination of the plots in Figure 4.1 shows the existence of trend breaks around the liberalization dates given in Table 1.1. However, there are further, and probably more significant, structural breaks in all indices. For instance, there is a clear indication of a shift in both level and trend around 1997, 98 in the stock price indices of all Asian countries, corresponding to Asian crises of this period. Based on this observation, the study reviews multiple structural breaks in order to consider them on the unit root tests. From a visual inspection of the plots in Figure 4.1, especially the break points, one may think that stock prices in all countries are trend-stationary processes, rather than random walk processes. Our empirical results show otherwise.

Country	ADF[a]	PP[b]
Argentina	-2.4700 [8]	-2.4692 [11]
Brazil	-3.1629 [8]	-3.3530** [12]
China	-3.1868 [7]	-3.1663* [11]
Hong Kong	-2.4260 [8]	-2.3631 [13]
Hungary	-1.8177 [9]	-1.9096 [11]
South Korea	-1.9673 [9]	-2.0107 [12]
Malaysia	-2.1368 [7]	-2.1651 [12]
Mexico	-3.8077 [3]	-3.5211* [11]
Philippines	-2.4790 [9]	-2.4462 [11]
Poland	-2.0637 [3]	-2.0215 [11]
Russia	-1.6367 [2]	-1.6387 [10]
Taiwan	-2.7494 [4]	-2.6863 [11]
Thailand	-1.4478 [9]	-1.4181 [12]
Turkey	-3.2129 [5]	-3.1510* [11]

Table 4.3 Unit root test results for the stock price indices.
Notes: Table reports the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests for the logarithm of the stock price indices. Test regressions include a constant a linear trend. Lag order for the ADF test and bandwidth for the long-run variance estimator of the PP test are given in brackets.
[a]Test allows a constant and a linear trend; 1%, 5%, and 10% critical values equal -3.973, -3.428, and -3.134, respectively.
[b]Test allows a constant and linear trend; 1%, 5%, and 10% critical values equal -3.95, -3.41, and -3.12, respectively.

We first apply the Augmented Dickey-Fuller (henceforth ADF) of Said and Dickey (1984) and Phillips and Perron (1992) (henceforth PP) unit root test to each series without breaks to garner results of standard unit root tests. The results are in Table 4.3. We first calculate the critical values of the ADF and PP tests using Monte-Carlo simulations calibrated for 20000 replications with a sample size T. For the ADF tests, we select the lag length, k, using the BIC, with the maximum lag length set to 30; while for the PP tests, the lag truncation lag automatically selected using Newey and West (1994) automatic selection with Bartlett kernel. The results reported in Table 4.3 indicate retaining the null hypothesis of a unit root at 1%, 5%, and 10% levels for all stock price series, except for China, Mexico, and Turkey for which the null hypothesis is rejected at 10% by the PP test and Brazil for which the null hypothesis is rejected at 5% by the PP test. Overall, the results obtained from both the ADF and PP tests suggest no significant evidence of mean reversion in emerging stock market indices. Both the ADF and PP tests will have low power, if the deterministic component is misspecified. The low power property of unit root tests in the presence of structural breaks, trends, and regime switching is examined in Campbell and Perron (1991), Diebold and Rudebush (1991), DeJong et al. (1992), Hassler and Wolters (1994), Lee and Schmidt (1996), and Nelson et al. (2001).

5. RESULTS FOR RANDOM WALK TESTS WITH STRUCTURAL BREAKS

This section investigates the impact of possible structural changes on the fractional integration properties of the stock price indices for each country, considering a constant term and a linear trend in the series. We explain the procedure we employ in the methodology section.

Table 1.2 presents the structural break dates estimated for each stock price index. In the empirical estimation, we allow seven maximum breaks, however results are not sensitive to number of brakes between five and ten. Results for five to a maximum of ten breaks are not reported to save space, but could be made available upon request from the authors. The number of breaks varies from five to seven. The structural break dates estimated for each country are generally consistent with the corresponding market liberalization dates, or explained by major economic events in the corresponding economies. Some break dates are very different across countries, while some dates are quite close. For all countries, a break occurs in either 2007 or 2008, which corresponds to the global recession started in 2007. For each of the five Asian countries (Hong Kong, South Korea, Malaysia, Taiwan, and Thailand), there is an evident break in 1997, corresponding to the Asian financial crises of 1997-98, except for Taiwan where the break occurs as late as 2000. The break dates reported in Table 1.2 coincide with abrupt changes in the emerging market stock indices apparent in Figure 4.1 and correspond to clearly identifiable market liberalization or financial crises.

Table 5.4 gives the values of d_0 where the null hypothesis cannot be rejected by the one sided test based on the statistics $\hat{r}$ defined in equation (3.4) for each of the stock price index series of the fourteen emerging markets considered. We compute the test statistics in the tables by assuming that u_t, the disturbances in equation (3.2), follows an ARMA(p,q) process. We estimate the ARMA(p,q) models, where $p, q \leq 6$. For each d value, we chose p and q lag lengths according to the BIC. For the stock price series, the null hypothesis H_0: $d = d_0$ in equations (3.1) and (3.2) with $d_0 = \{0.80, 0.81, \ldots, 1.19, 1.20\}$ will be tested. In order to save space we only report those values of $\hat{r}$ and the associated d_0 for which the null hypothesis H_0: $d = d_0$ are not rejected in Table 5.4. The second and third columns of the Table 5.4 correspond to the different assumptions for z_t, as indicated. $z_t = (1, t)'$ corresponds to the case of a constant and a linear time trend term, and $z_{1,t} = (1, t, DL_{t1}^{\tau l}, \ldots, DL_{tk}^{\tau l}, DT_{t,1}^{\tau l}, \ldots, DT_{t,k}^{\tau l})'$ is defined as the regressors in equation (3.1) with constant, time trend, trend and level shift dummy variables $DL_{t,j}^{\tau l}$ and $DT_{t,i}^{\tau l}$ for each structural break point $i = 1, \ldots, k$, where k is the endogenously determined number of simultaneous level and trend breaks. We define the dummy variables, DL for level shift and DT for trend shift, as: $DL_{t,j}^{\tau l} = 1$ if $t > T_{b,i}^{\tau l}$, 0 otherwise, and , $DT_{t,i}^{\tau l} = t - T_{b,i}^{\tau l}$ if $t > T_{b,i}^{\tau l}$, 0 otherwise, where $T_{b,i}^{\tau l}$ indicates the i^{th} structural break date.

The results reported in Table 5.4 evince that structural breaks have no impact on the integration order of the emerging market stock market price indices, except for one market. Only for Mexico, including structural breaks in the estimation changes the conclusion drawn from the case with a constant and linear trend. Interestingly, even when we account for all structural breaks selected by the procedure outlined above, 10 out of 14 markets show non-stationary and non- mean-reverting behavior, with four of the markets showing likely explosive structure. For all of these 10 markets, 95% confidence intervals cover the unit root case even when the structural breaks are taken into account, presenting evidence in favor of the weak form of the EMH.

Country	$z_t=(1,t)'$	$z_t=z_{1,t}$
Argentina	0.94^{a} (1.00) … [0.95^{*}] … **0.97^{b}** (-1.46)	0.92^{a} (1.38) … [0.94^{*}] … **0.95^{b}** (-0.97)
Brazil	0.94^{a} (1.40) … [0.96^{*}] … **0.98^{b}** (-1.29)	0.91^{a} (0.99) … [0.94^{*}] … **0.97^{b}** (-1.39)
China	1.04^{a} (1.22) … [1.06^{*}] … 1.08^{b} (-1.24)	1.01^{a} (1.63) … [1.04^{*}] … 1.06^{b} (-1.28)
Hong Kong	1.03^{a} (1.14) … [1.04^{*}] … 1.05^{b} (-0.82)	1.02^{a} (1.43) … [1.04^{*}] … 1.05^{b} (-1.34)
Hungary	0.98^{a} (1.30) … [1.00^{*}] … 1.02^{b} (-1.39)	0.96^{a} (1.24) … [0.98^{*}] … 1.00^{b} (-1.21)
South Korea	0.96^{a} (0.64) … [0.97^{*}] … **0.98^{b}** (-1.28)	0.93^{a} (0.95) … [0.94^{*}] … **0.96^{b}** (-1.60)
Malaysia	1.01^{a} (1.63) … [1.03^{*}] … 1.05^{b} (-1.28)	0.98^{a} (1.51) … [1.00^{*}] … 1.03^{b} (-1.55)
Mexico	0.97^{a} (1.11) … [0.99^{*}] … 1.00^{b} (-1.01)	0.94^{a} (1.33) … [0.96^{*}] … **0.98^{b}** (-1.20)
Philippines	1.00^{a} (0.88) … [1.01^{*}] … 1.03^{b} (-1.43)	0.96^{a} (1.47) … [0.98^{*}] … 1.00^{b} (-1.14)
Poland	1.03^{a} (1.55) … [1.06^{*}] … 1.08^{b} (-1.40)	0.98^{a} (1.23) … [1.01^{*}] … 1.04^{b} (-1.50)
Russia	1.01^{a} (1.27) … [1.03^{*}] … 1.05^{b} (-1.13)	0.97^{a} (1.45) … [1.00^{*}] … 1.03^{b} (-1.59)
Taiwan	1.05^{a} (1.49) … [1.07^{*}] … 1.09^{b} (-1.34)	1.03^{a} (1.22) … [1.05^{*}] … 1.07^{b} (-1.31)
Thailand	1.03^{a} (0.90) … [1.04^{*}] … 1.06^{b} (-1.62)	1.01^{a} (0.89) … [1.02^{*}] … 1.04^{b} (-1.35)
Turkey	0.99^{a} (1.13) … [1.01^{*}] … 1.03^{b} (-1.57)	0.96^{a} (1.08) … [0.98^{*}] … 1.00^{b} (-1.31)

Table 5.4 Fractional integration estimations of Robinson's (1994) score test statistic.

Notes: Table reports the lower and upper limits of the non rejection values at the five percent significance levels with corresponding value of the test statistic $\hat{r}$ defined in equation (3.4) given in parentheses. Table also reports, in brackets, the value of the d_0 that is not rejected at the minimum absolute value of the test statistic $\hat{r}$ defined in equation (3.4).

^{a} Lower bound of d_0 not rejected at the five percent significance level.

^{b} Upper bound of d_0 not rejected at the five percent significance level.

* The value that corresponds to the value of d_0 that produces the lowest statistics in absolute value across all d_0 values in the grid $d_0 = 0.80, (0.01), 1.20$. Bold values denote the cases where the upper bound of the 95% confidence interval does not cover a unit root, indicating stationarity.

We first examine the case for Argentina. The null hypothesis of $d = 0.80$ or $d = 1.20$ are both rejected in favor of a positive d in all cases for z_t with a constant, a linear time trend, and structural break dummies. However, the null hypothesis of $d =$ 0.94 as the lower limit and $d = 0.97$ is retained at 5% significance levels under the case $z_t = (1, t)'$. When we considered the case z_{1t} that considers structural breaks by including level and trend shift dummies, the values of d are not rejected at the 5% significance levels reduced to range from 0.92 to 0.95. These results suggest that, regardless of the consideration of structural breaks, we can reject the random walk model for the Stock Exchange Index series of Argentina.

We next consider the results for Brazil in Table 5.4. Under the case of $z_t = (1, t)'$, the null hypothesis of $d =$ 0.94 as the lower limit and d = 0.98 as the upper limit are retained, and, in the case of z_{1t}, the null hypothesis of d = 0.91 as the lower limit and d = 0.97 as the upper limit are retained. The evidence suggests that the Brazilian stock price index does not follow a random walk and is mean reverting, even when structural breaks are not taken into account. Therefore, the evidence does not support the weak form the EMH for Argentina and Brazil, since the stock market indices for these markets are, although non-stationary, long-memory and mean reverting processes.

For China, the null hypothesis of d as equal to 1.06, 1.07, and 1.08 is retained under the case for z_t with a constant, a linear time trend. However, when we consider the case of structural breaks by including trend shift and level shift dummies, the values of d not rejected at 5% are between 1.01 and 1.06. For China, the range of d values not rejected are above the unit root case $d = 1$, implying that the Chinese stock market is not mean reverting, even before not correcting for the impact of structural breaks.

The test results for the Hong Kong stock price index series given in Table 5.4 show retention of the null hypothesis for the d in the range from 1.03 to 1.05 when $z_t = (1, t)'$ and in the range from 1.02 to 1.05 when $z_t = z_{1t}$, implying that this series is not a mean reverting series. The test results indicate that the Hungary stock prices index follows a random walk process, regardless of accounting for structural breaks, because the null hypothesis that d is equal to 1.00 cannot be rejected for $z_t = (1, t)'$, and the same hypothesis is retained for the values of d between 0.96 and 1.00 after including structural break dummies.

The results reported in Table 5.4 for both cases indicate that the null hypothesis of a random walk can be rejected for South Korea, since the upper limit of the values of d retained under the null hypothesis is 0.98 and 0.96, for the cases of $z_t = (1, t)'$ and $z_t = z_{1t}$, respectively. Therefore, the evidence does not support the weak form of the EMH for South Korea and the stock price index for South Korea is a long-memory mean-revering process.

The null hypothesis that d is equal to 1.01, 1.02, and 1.03 cannot be rejected for Malaysia. For Mexico, under the case of no structural breaks, $z_t = (1, t)'$, the null hypothesis of $d = 1.04$ and $d = 1.05$ are retained. However, under the case of structural break dummies, z_{1t}, we observe that the d values not rejected under the null hypothesis are between 0.94 and 0.98. Therefore, evidence of random walk for the stock prices index of Mexico does not exist, implying that the Mexican stock price index series is a long-memory mean-reverting process and that evidence does not support the weak form of the EMH. The Philippines is another country for which consideration of structural breaks does not change the conclusion about the existence of random walk behavior. Therefore, the evidence supports the weak form of the EMH for the Philippines stock market. For Poland, the ranges of d values not rejected under the null are above or cover 1, regardless of the specification of a deterministic component. The evidence indicates that the Poland stock price index follows a non stationary process and is likely to show explosive behaviour.

The estimation results for Russia, Taiwan, Thailand, and Turkey are also presented in Table 5.5. For all of these countries, the unit root null hypothesis is not rejected irrespective of whether one includes structural break dummies or only allows a linear trend in the deterministic component. Therefore, we conclude that the stock markets of Russia, Taiwan, Thailand, and Turkey follow a random walk process even when one considers structural breaks, supporting the weak form of the EMH for these markets as well.

In short, except for two countries, we reject the mean reversion in stock price indices at a 5% significance level. For the exceptions, Hong Kong and Mexico, the range of fractional orders of integration not rejected when accounting for structural breaks is below one, supporting the mean reverting stock prices in these countries. However, the order of integration for these countries borders the unit root case, and strong evidence against the random walk does not exist. Therefore, we reject the mean reverting stock market price indices for 13 out of 15 countries. Overall, the weak form of the EMH is retained for emerging markets using the efficient fractional unit root test even after accounting for endogenously determined multiple structural breaks. In light of the results reported in Table 5.4, we conclude there is only weak evidence for Hong Kong and Mexico in favor of mean reversion in the stock market indices and the other markets considered in the study satisfy the conditions of the weak form of market efficiency on a daily basis. Moreover, this conclusion holds for seven countries after accounting for multiple endogenously determined structural breaks.

In order to estimate the appropriate order of integration more precisely, we re-compute the Robinson (1994) tests using a finer grid for values of $d_0 = 0.80, 0.81, \ldots, 1.12$. In this way, we construct an acceptable confidence interval for the null hypothesis of a unit root. Table 5.5 reports each time series, each type of regressor, and the confidence intervals of those values of d_0, where H_0: $d = d_0$ cannot be rejected at the 5% significance level. We construct these intervals as follows. First, starting from the first value of d in the grid, we form the statistic to test the null for this value. This value of d is discarded, if the null is rejected at the 5% level. Otherwise, the value is retained. We repeat this sequentially for all values of d in the grid, and then construct an interval between the lowest and highest non-rejection values of *d*.

	Argentina	**Brazil**	**China**	**Hong Kong**	**Hungary**	**South Korea**	**Malaysia**
Constant	5.20772***	5.92293***	2.86407***	2.95034***	2.70851***	-1.90939***	4.66057***
	(0.018703)	(0.015426)	(0.015672)	(0.011458)	(0.009221)	(0.008719)	(0.012177)
Trend	0.00046***	0.00208***	0.00411***	-0.00049***	-0.00078***	0.00074***	0.00161***
	(0.000069)	(0.000035)	(0.000075)	(0.000026)	(0.000023)	(0.000014)	(0.000047)
DL_{t1}^{d}	6.32581***	12.04455***	5.18978***	0.76757***	3.03554***	-1.24429***	4.90673***
	(0.010576)	(0.075648)	(0.033953)	(0.016981)	(0.027310)	(0.013529)	(0.032187)
DT_{t1}^{d}	-0.00002***	-0.00486***	-0.00020***	0.00181***	-0.00045***	-0.00025***	0.00001
	(0.000006)	(0.000075)	(0.000058)	(0.000012)	(0.000027)	(0.000007)	(0.000047)
DL_{t2}^{d}	17.18162***	4.33862***	3.56709***	10.60943***	0.95192***	-8.72922***	6.08111***
	(0.207026)	(0.081190)	(0.011006)	(0.078528)	(0.041418)	(0.051822)	(0.031666)
DT_{t2}^{d}	-0.00371***	0.00185***	0.00073***	-0.00259***	0.00146***	0.00246***	-0.00093***
	(0.000065)	(0.000053)	(0.000006)	(0.000033)	(0.000025)	(0.000016)	(0.000025)
DL_{t3}^{d}	2.80055***	4.09023***	6.32035***	1.82708***	2.78027***	1.91190***	0.44008***
	(0.050698)	(0.023915)	(0.042929)	(0.024145)	(0.057490)	(0.052691)	(0.084678)
DT_{t3}^{d}	0.00080***	0.00137***	-0.00035***	0.00084***	0.00025***	-0.00045***	0.00234***
	(0.000012)	(0.000008)	(0.000013)	(0.000007)	(0.000025)	(0.000012)	(0.000047)
DL_{t4}^{d}	-1.90605***	10.16074***	-8.48552***	1.38395***	0.16137***	2.80855***	3.52104***
	(0.183817)	(0.077353)	(0.173031)	(0.014543)	(0.043940)	(0.078365)	(0.012382)
DT_{t4}^{d}	0.00155***	-0.00030***	0.00342***	0.00072***	0.00108***	-0.00051***	0.00061***
	(0.000035)	(0.000018)	(0.000041)	(0.000002)	(0.000014)	(0.000014)	(0.000004)
DL_{t5}^{d}	2.58164***	-0.40623***	6.54969***	2.04171***	2.35409***	-12.80895***	25.36664***
	(0.193677)	(0.065324)	(0.039660)	(0.158475)	(0.053077)	(0.157728)	(0.213091)
DT_{t5}^{d}	0.00064***	0.00168***	-0.00012***	0.00059***	0.00058***	0.00191***	-0.00427***
	(0.000032)	(0.000011)	(0.000007)	(0.000017)	(0.000013)	(0.000025)	(0.000045)
DL_{t6}^{d}		-9.17523***		1.64593***	-9.26843***	-6.53964***	-5.86679***
		(0.615205)		(0.071931)	(0.329608)	(0.040281)	(0.235420)
DT_{t6}^{d}		0.00282***		0.00056***	0.00283***	0.00083***	0.00214***
		(0.000090)		(0.000007)	(0.000069)	(0.000005)	(0.000046)
DL_{t7}^{d}		15.06097***		5.41230***	6.37401***	-3.56037***	2.98389***
		(0.149705)		(0.108582)	(0.057209)	(0.075471)	(0.014816)
DT_{t7}^{d}		-0.00062***		0.00020***	-0.00034***	0.00042***	0.00038***
		(0.000020)		(0.000009)	(0.000010)	(0.000008)	(0.000002)
AR(1)	-0.02576**	0.03544***		0.83315***		0.63365***	0.10030***
	(0.012377)	(0.011054)		(0.054247)		(0.084111)	(0.010471)
AR(2)	-0.09430***			-0.03007***			
	(0.012376)			(0.011509)			
AR(3)				0.03971***			
				(0.009552)			
MA(1)				0.80894***	-0.07063***	0.68486***	
				(0.053736)	(0.012711)	(0.079222)	

(continued on the next page)

	Mexico	Philippines	Poland	Russia	Taiwan	Thailand	Turkey
Constant	4.14221***	1.75000***	6.73693***	4.08785***	2.83952***	1.52357***	8.73818***
	(0.008616)	(0.013374)	(0.012175)	(0.013926)	(0.011859)	(0.012957)	(0.022001)
Trend	0.00173***	0.00501***	-0.00083***	0.00396***	0.00089***	-0.00042***	-0.00372***
	(0.000017)	(0.000052)	(0.000047)	(0.000048)	(0.000039)	(0.000038)	(0.000110)
$DL^{d}_{t,1}$	5.39507***	3.41140***	2.20961***	8.95788***	1.18609***	2.27984***	5.89590***
	(0.021191)	(0.019780)	(0.048434)	(0.076831)	(0.037332)	(0.008969)	(0.058138)
$DT^{d}_{t,1}$	0.00071***	0.00043***	0.00918***	-0.00505***	0.00445***	-0.00025***	0.00604***
	(0.000015)	(0.000023)	(0.000078)	(0.000120)	(0.000048)	(0.000005)	(0.000110)
$DL^{d}_{t,2}$	5.15777***	1.81597***	9.06356***	1.60862***	3.65771***	-2.75998***	11.04643***
	(0.014404)	(0.031501)	(0.043953)	(0.045165)	(0.066392)	(0.055688)	(0.045195)
$DT^{d}_{t,2}$	0.00039***	0.00123***	-0.00086***	0.00298***	0.00177***	0.00161***	-0.00205***
	(0.000005)	(0.000019)	(0.000043)	(0.000043)	(0.000055)	(0.000016)	(0.000044)
$DL^{d}_{t,3}$	1.71903***	4.46629***	8.79152***	3.30213***	5.34607***	0.72534***	8.48878***
	(0.031485)	(0.041733)	(0.013840)	(0.013813)	(0.031362)	(0.046628)	(0.021499)
$DT^{d}_{t,3}$	0.00119***	0.00009***	-0.00022***	0.00136***	-0.00013***	0.00062***	0.00032***
	(0.000007)	(0.000016)	(0.000006)	(0.000006)	(0.000017)	(0.000010)	(0.000009)
$DL^{d}_{t,4}$	-2.63231***	6.42933***	3.72956***	1.29896***	5.17990***	24.57127***	22.08428***
	(0.301554)	(0.036637)	(0.029479)	(0.097901)	(0.020488)	(0.189777)	(0.241883)
$DT^{d}_{t,4}$	0.00181***	-0.00076***	0.00146***	0.00155***	0.00009***	-0.00374***	-0.00371***
	(0.000054)	(0.000010)	(0.000008)	(0.000026)	(0.000006)	(0.000033)	(0.000072)
$DL^{d}_{t,5}$	6.77814***	-1.74855***	31.68341***	8.38334***	3.49407***	3.89053***	4.00142***
	(0.075305)	(0.044061)	(0.384934)	(0.110794)	(0.026136)	(0.086093)	(0.049440)
$DT^{d}_{t,5}$	0.00019***	0.00106***	-0.00488***	-0.00025***	0.00034***	-0.00026***	0.00128***
	(0.000012)	(0.000009)	(0.000084)	(0.000024)	(0.000005)	(0.000013)	(0.000011)
$DL^{d}_{t,6}$		-1.37322***	8.59935***		-1.82560***	-0.40485***	26.87611***
		(0.050192)	(0.047413)		(0.149138)	(0.086867)	(0.438517)
$DT^{d}_{t,6}$		0.00089***	0.00018***		0.00110***	0.00042***	-0.00311***
		(0.000008)	(0.000009)		(0.000023)	(0.000011)	(0.000082)
$DL^{d}_{t,7}$					3.48623***	-4.61267***	9.96817***
					(0.156624)	(0.084384)	(0.087995)
$DT^{d}_{t,7}$					0.00029***	0.00085***	0.00008***
					(0.000021)	(0.000009)	(0.000014)
AR(1)	0.54648		0.41078***	0.13348***	0.63198***	0.10373***	
	(0.557625)		(0.089243)	(0.014099)	(0.092839)	(0.009825)	
AR(2)	-0.11407						
	(0.083470)						
AR(3)	0.03749						
	(0.027669)						
MA(1)	0.39691	-0.12361***	0.29570***		0.57129***		-0.08498***
	(0.557910)	(0.011488)	(0.093505)		(0.098322)		(0.011960)

Table 5.5 Estimates of the deterministic and ARMA parameters.
Notes: Standard errors of the estimates are given in parentheses. *, **, *** denote significance at 1%, 5%, and 10% levels, respectively.

Table 5.5 also presents the confidence intervals for the two cases of deterministic regressors. In the first case, we ignore structural breaks and allow only for a constant and a linear trend. The second case includes structural break variables in the deterministic component in order to remove the impact of shifts in the mean and growth rate. We model the stochastic part of the series as a linear ARMA process. As before, the moving average and autoregressive orders of the ARMA models are determined using the BIC by Beran et al. (1998). The BIC consistently estimates the order of the pure AutoRegressive (AR) models when the fractional integration order d is treated as an additional parameter. In our case, d is not estimated and needs not be treated as an additional parameter.

From the second and third columns of Table 5.5, we observe that the values are very similar, independent of the inclusion of structural break variables, which suggests that structural breaks do not significantly affect the integration properties of daily stock price indices. The upper limits of 95% confidence intervals all exceed 1 when considering only a constant and a linear trend, except for Argentina, Brazil, and South Korea for which lower limits are below 1. The confidence intervals range from the lowest lower limit of 0.94 (Argentina and Brazil) to the highest upper limit of 1.09 (Taiwan). The lower limits exceed 1 for 8 countries. The values at the minimum absolute value of the statistics, reported in brackets between the lower and upper limits, are equal to or exceed 1 for 10 of the 14 countries. The upper limits are below 1 for Argentina, Brazil, and South Korea, implying that the EMH does not hold for the stock markets of these countries even when structural brakes are not taken into account.

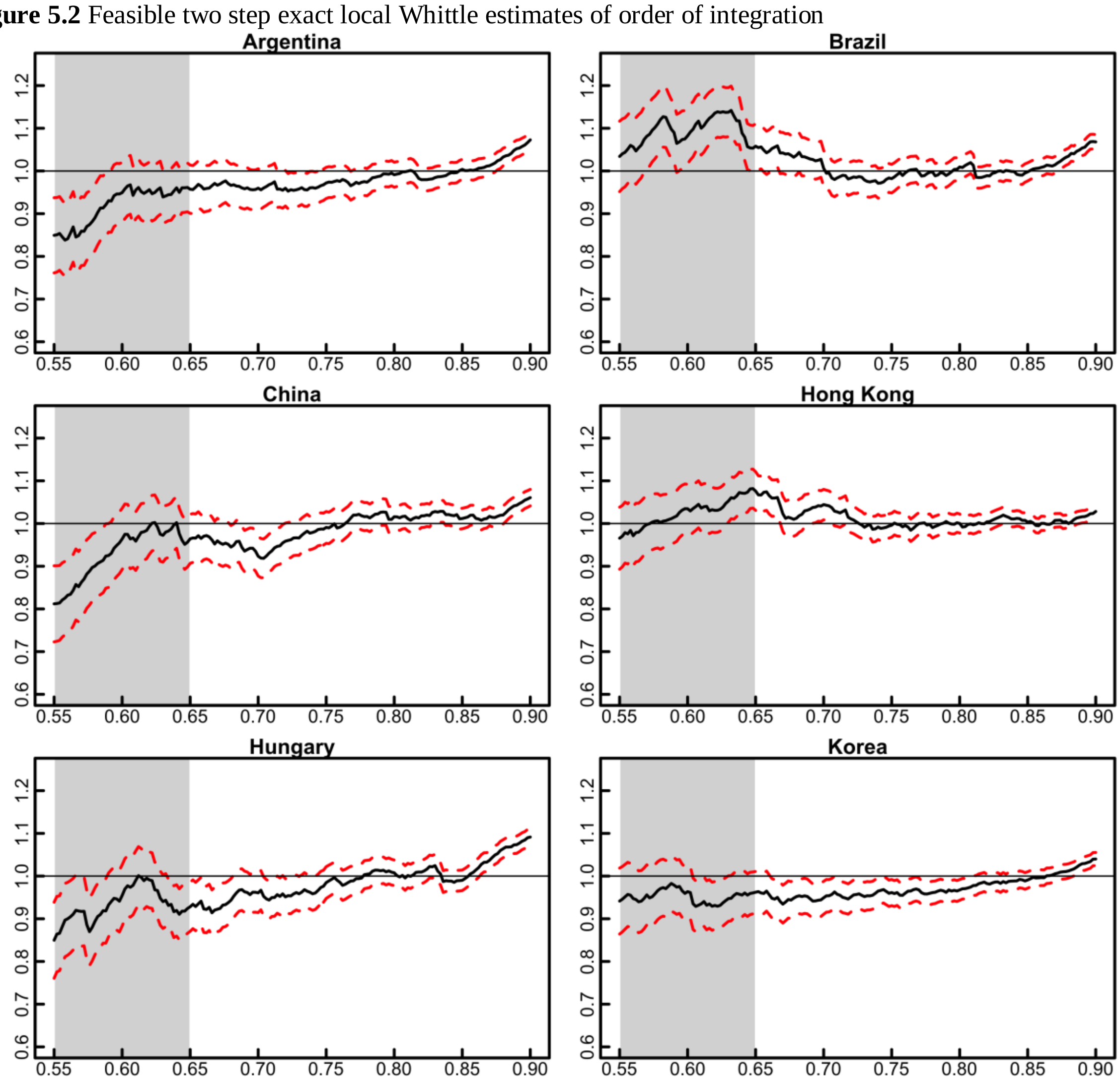
When we include the structural break regressors in the deterministic component, we observe a marginal reduction in both the upper and lower limits of 95% confidence intervals. However, the 95% confidence intervals cover the unit root cast of $d = 1$ for 10 countries. The upper limit of the confidence intervals are 0.95, 0.97, 0.96, and 0.98, respectively for Argentina, Brazil, South Korea, and Mexico, indicating that the daily stock price index of these countries are mean reverting and the weak form of efficiency does not hold. For the remaining 10 countries the results are analogous to cases not considering structural breaks. Lower confidence limits range from 0.91 (Brazil) to 1.03 (Taiwan), while upper limits range from 1.0 (Argentina, Brazil, South Korea, and Mexico) to 1.07. The d values obtained at the minimum absolute value of the statistics are equal to or above 1 for seven countries. In summary, we obtain evidence in favor of the unit root hypothesis for 10 out of 14 countries even after accounting for multiple endogenously determined structural breaks. Thus, the evidence in favor of weak efficiency at a daily frequency for emerging stock markets derives from confidence intervals constructed with non-rejection values of fractional integration orders.

Table 5.5 reports the estimates of the parameters for constant, linear trend, structural break dummies, and ARMA parameters of the models with deterministic specification $z_{1,t} = (1, t, DL_{t,1}^{\tau l}, ..., DL_{t,k}^{\tau l}, DT_{t,1}^{\tau l}, ..., DT_{t,k}^{\tau l})'$. The estimates of the all level and trend break dummies are significant at 1% significance level for all stock market indices. The significant break dummy estimates point to the existence of structural breaks in all stock market indices, strengthening the inclusion of structural break dummies in our empirical analysis.

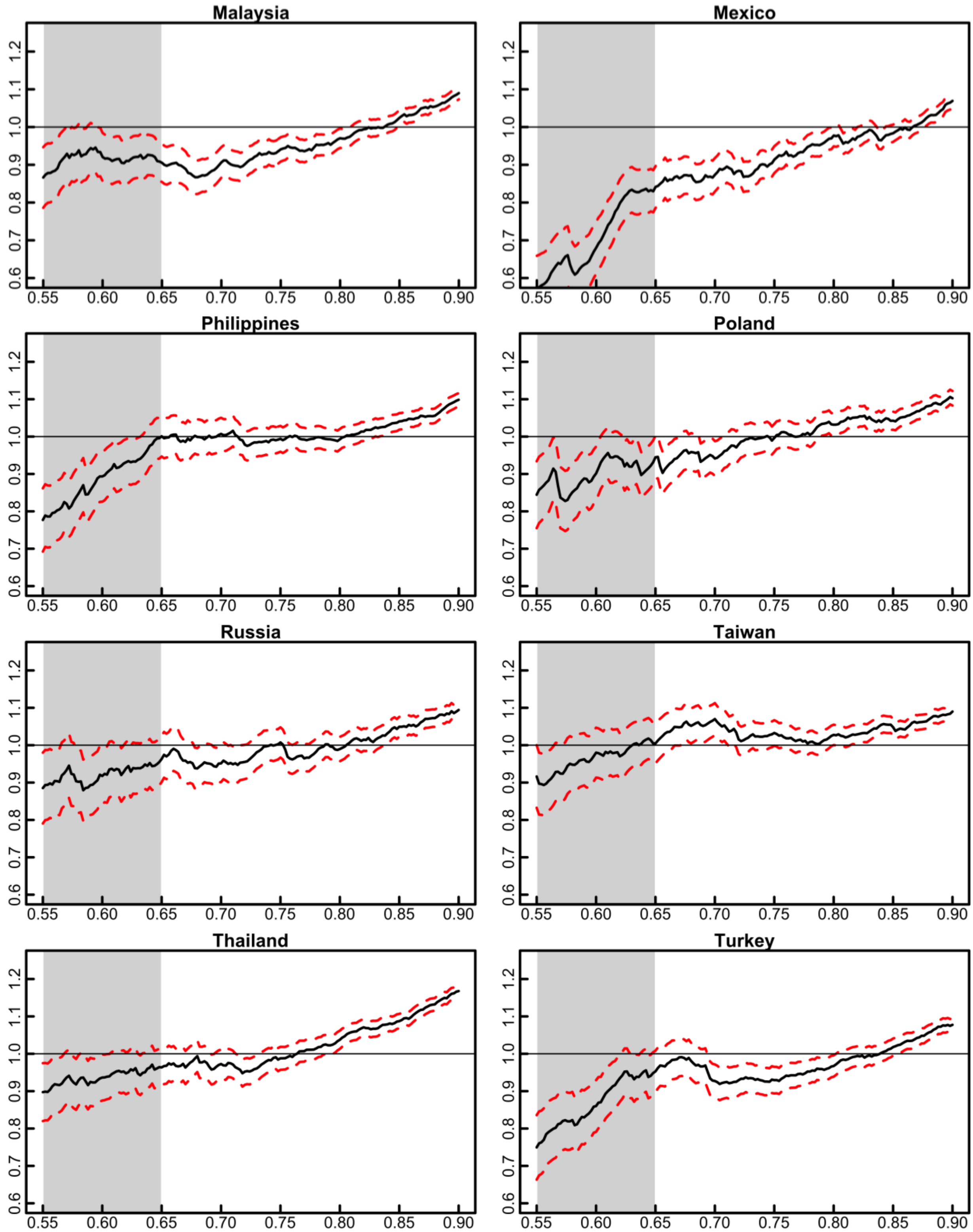
The evidence from Robinson's (1994) parametric method indicates that stock price indices of 14 emerging markets, except Argentina, Brazil, South Korea, and Mexico, integrate with orders of 1 or above. In order to investigate the robustness of our results, we estimate the fractional order of integration using the semi-parametric FELW2ST of Shimotsu (2010). Semi-parametric estimation of the fractional integration order d has appeal in empirical work, because it is disinterested about the short-run dynamics of the process, and hence robust to its lack of specification. We have to choose the bandwidth parameter m, which controls the number of periodogram ordinates included in the estimation, in order to estimate d using the FELW2ST. A general optimal bandwidth choice is not available; instead $m = T^{\alpha}$ with $\alpha = 0.60$ or $\alpha = 0.65$ is commonly used. Here, we estimate d as $\alpha = 0.50, (0.002), 0.90$.

Figure 5.2 reports the results for each stock index series based on the FELW2ST estimate, where the estimate $\hat{d}$ covers a range of values of $m = T^{\alpha}$ with $\alpha = 0.50, (0.002), 0.90$. In each plot, the most commonly used bandwidth in applications, which corresponds to $\alpha \in [0.55, 0.65]$, is shaded. Figure 5.2 also shows the 95% confidence intervals corresponding to the I(1) null hypothesis. We observe that, for 13 of the series, the 95% confidence interval for d covers the unit root case $d = 1$ when $\alpha \in [0.55, 0.65]$. The only exception to this result is Mexico for which the interval covers $d = 1$ only after $\alpha > 0.80$. This finding implies that the hypothesis of unit root cannot be rejected for 13 out of 14 daily stock indices of emerging markets for the most commonly preferred ranges of the bandwidth parameter. This finding is consistent with the results obtained from Robinson's (1994) procedure that these series do not present mean reverting behavior, except for Argentina, Brazil, and South Korea for which Robinson's (1994) procedure indicates mean-reversion. The estimates are lower than 1 when $\alpha < 0.60$ for all countries except for Brazil and South Korea. For Mexico, the 95% upper limit estimates of d are below 1 until $\alpha > 0.80$. The estimates of the order of integration are all above 1 for α values in the range [0.52, 0.70] for Brazil. In general, the estimates of d exceed 1 for ranges of bandwidth parameter α above 0.80. A final remark about the estimates of order of integration is that we are unable to reject the I(1) hypothesis for all stock market indices when $\alpha > 0.60$, except Mexico, which rejects the I(1) hypothesis for $\alpha > 0.80$. In summary, the evidence from the FELW2ST approach indicates that, except for Mexico, daily stock price indices of 13 emerging markets are not mean reverting even after considering the effect of endogenously determined structural breaks and complementing the results from Robinson's (1994) efficient test. Thus our results are robust to the specification of the short memory component in Robinson's (1994) efficient testing approach.

Figure 5.2 Feasible two step exact local Whittle estimates of order of integration



(continued on the next page)



Notes: Each graph plots estimates of d based on the FELW2ST approach (Shimotsu, 2010). The horizontal axis corresponds to the parameter α that sets bandwidth to $m = T^{\alpha}$, while the vertical one refers to the order of integration. Straight lines represent estimates of order of integration d, while the dashed lines correspond to 95% confidence limits.

6. CONCLUSION

This study contributes to the literature with methodological innovation that accounts for multiple endogenously determined structural breaks when testing for random walk stock prices, as well as supporting the weak form of the efficient market hypothesis (EMF) in the context of emerging stock markets. The standard tests, such as Dickey and Fuller (1979, 1981), and Phillips and Perron (1988), for the random walk hypothesis in stock prices have low power against the alternative hypothesis of mean reversion in small samples when the underlying series presents structural breaks. The tests favor retaining the unit root null hypothesis when structural changes in the underlying series exist. Failure to account for the breaks can produce misleading tests and result in incorrect inferences. In this paper, we implement the Robinson (1994) efficient test statistics for a random walk that allows us to account for the effects of structural changes in stock prices. This test considerably improves the power over the ADF and PP tests in a given sample size. Our approach extends Robinson's (1994) efficient test of unit root against fractional integration to allow for multiple endogenously determined structural breaks. In almost all cases, we find support for the random walk hypothesis. For only four stock markets, weak evidence of mean reverting long memory stock prices exists. We check the robustness of our results using the semi-parametric FELW2ST estimator of Shimotsu (2010). The FELW2ST estimator allows polynomial trends, non-normal distributions, and consistency for non-stationarity orders of integration. The results from the FELW2ST approach show that, except for Mexico, stock price indices of 13 emerging markets are not mean reverting. Thus, our results from Robinson's (1994) efficient test are robust to misspecification of the short memory component.

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