An Entropy Approach to Measure the Dynamic Stock Market Efficiency

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Abstract
We measure stock market efficiency by drawing the comprehensive sample from Asia, Europe, Africa, North–South America, and Pacific Ocean regions and rank the cross-regional stock markets according to their level of informational efficiency. The study period spans from January 1, 1994, to August 3, 2017. We employ the approximate entropy approach and find that stock market efficiency evolves over the period. The degree and nature of evolution vary across regions and the development stage of the markets. The global, regional, domestic economic, and non-economic factors influence the adaptive nature of the stock markets. The emerging stock markets have improved efficiency by financial liberalization policy but are adversely affected by global shocks. The estimates validate the relevance of the adaptive market framework to describe the rejection of random walk without excess returns. The results suggest the growing presence of technical analysis and active portfolio managers. The emerging markets in Asia hold policy lessons for their peers. The findings suggest that global investors need to overcome the homogeneity bias as returns opportunities exist within the region and types of markets.

Keywords  EMH · Entropy · AMH · Adaptive markets · Financial crises · Portfolio management

JEL Classification  G14 · G4 · G10 · G01

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Introduction

Informationally efficient markets are indispensable for the efficient allocation of capital, investment, risk & portfolio management decisions. Ostensibly, a large volume of research tests the efficient market hypothesis (EMH), but conclusive evidence is elusive. The assertion of EMH as dated research is a blindside view, whereas the need is to examine it as a dynamic system. We need to view informational efficiency as a dynamic mechanism, whereas empirical research on EMH confines it to a static theory. The rejection of random walk does not necessarily imply profitability (Canarella et al. 2013), nor markets are efficient over the period (Campbell et al. 1997). Instead, informational efficiency is relative and possibly varies over the period and across the markets. Several factors, including financial liberalization, domestic macroeconomic policy, accounting standards, market regulations, tax structure, and political environment, among others, influence the efficiency of markets (Rejeb and Boughrara 2013; Hooy and Lim 2013; Stoian and Iorgulescu 2020; Lin et al. 2021; Liu and Li 2021; Galvani and Ackman 2021). The previous research on testing of stock market efficiency hardly captures these changes.

Moreover, underdeveloped markets have been continuously pursuing capital market reforms to improve the informational efficiency of markets. These reforms are self-defeating when empirical research confines to conclude markets as either efficient or inefficient over the period. The role of financial innovations in making the market complete is ruled out in such a static framework. The microstructure reforms and automation significantly changed the market structure, competition, and trading environment. These changes affect the behavior of investors and, eventually, the returns (Hasbrouck 2007). Financial analysts need to recognize the existence of new paradigms and go beyond trading on the information (O’Hara 2014).

Therefore, the previous research is not only less relevant for trading strategies or regulation but hardly explains the nuances of the markets and the presence of technical analysts and active portfolio managers in the industry (Brown 2020). The weak form of efficiency demands a new empirical investigation in a dynamic system. In this light, we attempt to measure the level of informational efficiency over the period and across the markets. We also investigate the factors influencing the evolution of markets in developed and emerging economies. We offer intriguing insights into the working of markets and trading strategies. The analysis also suggests measures for the better functioning of the markets.

Informational efficiency is critical for investors to access complete and accurate information from the market. In an informationally efficient market, asset returns reflect all available information instantaneously and correctly. Such a mechanism rules out arbitrage opportunities and leaves no scope for excess returns (Fama 1970). In an informationally efficient stock market, active portfolio management is futile, whereas a simple strategy of buying and holding diversified securities is enough in such markets. Nevertheless, the increasing importance of active portfolio

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1 For a detailed review on testing efficiency, see, Lo (2017).
management and high-frequency trading combined with algorithmic trading speaks otherwise. Our research deciphers the dynamism of the markets and empirically attempts to reconcile the presence of active portfolio management and EMH.

We contribute to the extant literature in several ways. We measure the degree of stock market efficiency in a weak form and examine whether the degree of efficiency is time-varying following unique approaches. We focus on the evolution of stock market efficiency over the years across the globe. A sizeable number of studies document episodes of stock market efficiency (e.g., Cajueiro and Tabak 2005; Ito and Sugiyama 2009; Charfeddine and Khediri 2016; Charfeddine et al. 2018). These studies reject or validate EMH during a particular period. These studies focus on fixed windows. Besides, the pertinent literature ignores the varied characteristics of the markets and does not capture time-varying complexities. The inferences from such analyses are seldom helpful in understanding the evolution of the markets, particularly the EMs across the regions.

Moreover, the extant evidence on the developed markets (DMs). The literature on the comparative analysis between DMs and EMs across the regions over 3 decades is not available. Also, the previous work hardly explains the implications of time-varying efficiency for trading, which makes the present analysis unique. Besides, the previous evidence on episodic efficiency was sensitive to the chosen window size. The analysis of market efficiency in a single rolling window framework is biased to capture the market dynamism in different periods (Alvarez-Ramirez et al. 2012; Verheyden et al. 2015). We assess the cross-regional market efficiency in the alternative rolling window lengths and find the change in the market dynamics as per the change in the window size. The findings of our study suggest that investors need to exploit the price pattern in different possible time windows before investing in any particular market to ensure effectiveness of trading strategies as profitable opportunities are limited to very brief periods.

Further, we employ the approximate entropy approach to assess the level of time-varying efficiency, which has seldom been explored before. In the past, several methods, such as autocorrelation tests, unit root tests, and a battery of linear & non-linear approaches, were applied to examine the weak form of efficiency. However, these methods fall short in measuring the degree of market efficiency. At best, these approaches reject or accept the null of the random walk hypothesis (RWH). Therefore, our definition of stock market efficiency is based on the degree of complexities in the patterns contained in a random sequence of price changes. The approximate entropy allows us to measure the degree of randomness and predictability. The entropy method is efficient in the presence of noise and possesses better power properties. Wang et al. (2012) and Alvarez-Ramirez et al. (2012) utilize the entropy approach to probe foreign exchange markets and the US stock market, respectively. The research deciphering the varying degree of complexities in the stock returns of diversified market conditions is unavailable.

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2 For a detailed survey, see, Hiremath (2014).
3 Theodore (1996) considers such exploitable patterns of the price changes as the primary practice of market practitioners.
Departing from the previous research, we measure the degree of stock market efficiency across the regions and types of markets. A disaggregated analysis of informational efficiency provides a captivating understanding of the working of market forces in various regions and allows a meaningful comparison. Unlike previous work, we rank the stock markets across the region and type of markets based on diversities in their price patterns. We also follow a cluster approach to ensure the robustness of our inferences.

Further, an inquiry into the influence of the economic and non-economic factors on the evolution of the stock market efficiency over 3 decades fills an essential gap in the pertinent literature. We develop an adaptive market framework to examine the time-varying efficiency. AMH research remains in infancy despite its theoretical importance (see, Hiremath and Kumari 2014). The pertinent studies employ conventional tests and do not measure the degree of efficiency. The markets with the institutional, regional, and developmental heterogeneity are under-researched, which primarily motivates us to assess AMH. Our research significantly extends the literature on efficiency, liberalization, and emerging markets (EMs).

In this empirical research, we find a varying level of efficiency across the markets. We find the European stock markets as the most efficient, whereas the economic reforms and investment in market infrastructure significantly improved the degree of efficiency in EMs. We show the influence of several factors, including economic and non-economic events, on the evolution of stock market efficiency. Our analysis offers insights into capital market development plans.

The rest of the paper is organized into the following sections: “Theoretical underpinnings and empirical methods” discusses the conceptual framework and the entropy method. “Empirical results” presents discussion and implications of results. The final section concludes the paper.

**Theoretical Underpinnings and Empirical Methods**

We develop an adaptive market framework to examine the time varying efficiency and identify the factors influencing the evolution of the markets. Our entropy approach captures the complexities of the data generating process, which explains the conundrum of contradictory evidence on stock market efficiency.

**Conceptual Framework and Related Research**

The testing of market efficiency often misleads the investors from the actual inferences of the market due to its inability to capture the dynamic information environment. The stock market efficiency cannot be static over the period due to several institutional and regulatory changes and financial innovation. In addition, several events also influence the information and its analysis both positively and adversely. Hence, Campbell et al. (1997) emphasize the relative efficiency of stock markets.
Various studies examine such relative efficiency in several markets (Zalewska-Mitura and Hall 1999; Griffin et al. 2009; Ito and Sugiyama 2009; Hiremath and Kamaiah, 2010) by testing the RWH. The research on time-varying efficiency primarily focused on developed markets (DMs) and offered little on EMs except concluding them as inefficient (Hiremath 2014). The research on relative efficiency also lacks a rigorous conceptual framework. Moreover, the essence of time-varying efficiency remained controversial due to the divergent views from neoclassical and behavioral schools on the nature of efficiency.

Against this backdrop, the adaptive market hypothesis (AMH) of Lo (2004) offers a theoretical foundation to dynamism in informational efficiency. Under AMH, the market evolves over the period. The market behaves as an evolutionary system in which the market participants are motivated by bounded rationality. In this context, AMH explains dynamism in informational efficiency – deviation of the security prices from the equilibrium. The extent of information incorporation in adaptive markets depends on the market environment and the nature of the participants. Non-synchronous trading, high transaction costs, poor accounting standards, lack of disclosure norms, and poor corporate governance are the characteristics of EMs. The EMH, which assumes a frictionless market, hardly captures the intricacies of information aggregation in EMs. The AMH accommodates all the market frictions, including behavioral biases. Thus, AMH depicts a realistic picture of the markets, and the framework is relevant to understanding the trading inferences.

Despite the fierce debate, no consensus on the behavior of the financial market and portfolio management is reached (Lo 2005). Although the literature on behavioral biases successfully explains the market anomalies and role of beliefs, biases, and investors’ sentiment, an alternative framework that convincingly reasons the empirical puzzle of the unpredictability of returns despite deviation of asset returns from the EMH is lacking. Lo (2005) uses an evolutionary approach of Farmer and Lo (1999) and Farmer (2002) to study interactions in financial markets and asserts that ‘dynamics of evolution, i.e., competition, mutation, reproduction, and natural selection determine the efficiency of markets. In AMH, the market is like a biological environment; various kinds of investor groups are distinct species. The interaction of such species with the environment (or ecology) determines the degree of information that eventually reflects in prices. The profit opportunities are similar to that of food and water in ecology. The availability and magnitude of these opportunities dictate the level of competition in the market. Hence, the profits and losses are subject to the market conditions and the number of entry and exit of investors. The successful traders survive in the market, whereas unsuccessful traders eventually extinct (exit) after losses beyond the bearable point. Thus, the survival of the richest and the law of natural selection determines the market’s evolution. In an adaptive market, fit and adaptable are relevant than rationality and biases.

In liberalized economies, the continuous occurrences of the dynamic economic events, changes in the market microstructure, uncertain behavior of the market participants, and costly information infuse dynamism in the market environment. The changing information situation drives away the asset prices from the random-walk benchmark and allows the market dynamics to adapt optimally. Accordingly, the level of stock market efficiency varies over time and across the region based on its adaptability to dynamic economic situations, which motivates us to use AMH as an
underlying theory in assessing the pricing part of informational efficiency across the regions over 3 decades. Further, the adaptability of the domestic stock market not only depends on the domestic but also on the external factors in a globalizing world. Underdeveloped economies have been introducing economic and microstructure reforms to improve the quality of the financial markets. Our conceptual framework allows us to capture these changes and explain their influence on the evolution of developing markets.

The evolutionary perspective of market efficiency does not necessarily imply the random-walk stock returns. Moreover, the static all-or-nothing market condition remains invalid in an efficient market under the adaptive framework. Therefore, the combined analysis of the dynamic price patterns and adaptability of agents to the changing economic and non-economic environments provide a base for measuring stock market efficiency under AMH. From a macroscopic viewpoint, approximate entropy efficiently deals with diversities and variations in the price patterns exhibited by the market under a dynamic information environment. The method further possesses better power properties to deal with the financial noise (Pincus and Kalman 2004). In this aspect, our estimation of the approximate entropy approach in a rolling window framework and analysis of the cross-regional factors associated with each entropic variation of the markets provides a better assessment of the informational efficiency under the adaptive market framework. Accordingly, our definition of informational efficiency is based on the degree of time-varying complexities in the patterns in a random sequence of price changes, which provides an efficient estimate for AMH across the regions. The properties of approximate entropy efficiently capture the complexities of the stock returns, and hence a composite index of various methods is not appropriate to address the current research problem. The AMH discusses the complexities of the evolving market system, and hence the investors often do not beat the market despite the presence of excess returns. The approximate entropy is appropriate to capture these complexities.

**Model Specifications and Data**

We employ the approximate entropy (APEn) proposed by Pincus (1991) and Pincus and Kalman (2004) to assess the extent of randomness in the returns series \( r_t \). APEn calculates the likelihood of \( r_t \) series with \( m \) dimension that remains similar on the next incremental (i.e., \( m + 1 \)) dimensions and investigates the regularity of the \( r_t \) series. In finance, APEn has the advantage of measuring financial market efficiency by analyzing the diverse patterns and statistical variations of the return \( r_t \) series at a finite length. Therefore, APEn is one of the best measures to assess market randomness (Pincus and Kalman 2004). Various methods, such as linear serial correlation analysis, unit-root tests, variance ratio tests, state-space estimates, and Hurst exponents, were employed in the previous work to examine the random-walk properties of the financial time series.\(^4\) Nevertheless, these tests do not possess statistical

\(^4\) For a discussion on various methods to test efficiency, see Hiremath (2014).
power properties when the underlying data series is noisy. Also, these methods are inefficient in capturing the complexities of high-dimensional systems.

The entropy methods possess better statistical power properties to quantify the complexities in stock price patterns and efficiently capture the market irregularity due to new information processing (Gulko 1999). Besides, the entropy also identifies the nonlinear dependence in the series (Darbellay and Wuertz 2000). Since the seminal work of Clausius (1865), several entropy methods such as Shannon entropy (Shannon 1948), relative entropy (Kullback and Leibler 1951), Kolmogorov complexities (Kolmogorov 1968), E-R entropy (Eckmann and Ruelle 1985), and Permutation entropy (Bandt and Pompe 2002) are developed to examine the complexities of the time-series data.

Unlike the traditional entropy approaches, which are biased in examining the system noise, the APEn approach efficiently deals with the noise by making data comparisons possible on a larger scale. APEn has an advantage over other methods in examining the time-varying complexities of the system as it computes the statistical variations of $r_t$ at a finite length. Therefore, APEn is the indicator of financial market stability (Pincus and Kalman 2004). Another unique strength of APEn lies in its ability to distinguish different systems, namely high and low dimensional chaotic systems, periodic and multi-periodic systems, a hybrid and stochastic system with a simple algorithm. This ability ensures the robustness of the inferences (Sleigh and Donovan, 1999). APEn also computes the irregularity of less-frequently analyzed systems with the correlated and non-identically distributed random variables in an unbiased manner (Pincus 1991). Given these unique advantages, we choose APEn to examine the stock market complexities with 500 random sequences across the regions. Therefore, our findings on the behavior of stock returns are unique and robust.

For a given stochastic variable $(r_t)$, the time series $(T_s)$ with length $N$ takes the following form:

$$\{r_j\} = \{r_1, r_2, r_3, \ldots, r_N\}$$

(1)

In Eq. (1), length $N$ is related to a time scale $\tau = NT_s$. For a given $T_s$ with $N$ observations, we set the APEn algorithm with the two specified parameters: embedding dimension ($m$) and tolerance level ($r$). The former represents the length of a pattern, whereas the latter explains tolerance for the similarity between the patterns. Hence, we set $m=2$ and $r=0.15$ in the APEn estimation for finite data length of $N=6154$.\(^5\) Therefore, we create two $m$-dimensional sequence vectors [i.e. $X^m(i), X^m(j)$] in the first step.

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\(^5\) Our selection of $m$ and $r$ is consistent with the literature. According to Yentes et al. (2013), APEn increases the self-matches with the increase in data length, and such self-matching bias can only be controlled with $m=2$ and $r \geq 0.15$. They argue that the value of entropy is stabilized with greater $N$. The minimum threshold for $N$ must be greater than 200 data points. Lu et al. (2008) document that smaller $r$ leads to the few self-matches due to low-pass filter. APEn estimation with 0.15 tolerance level is not biased by the increase or decrease in self-matches in the $T_s$ series. The estimates of the entropy with 0.1 and 0.2 tolerance levels are not reported in to save the space.
where \( i \neq j \) and \( 1 \leq i \) and \( j \leq N-m+1 \).

In the second step, we compute the distance between the two vectors by calculating the absolute difference between their respective scalar components as follows:

\[
d[X^m(i), X^m(j)] = \max_{k=0, \ldots, m-1} \{ |x(i+k) - x(j+k)| \},
\]

where \( 0 \leq k \leq m-1 \).

The distance between the respective scalar components calculates the match between \( X^m(i) \) and \( X^m(j) \). The two embedded vectors remain similar if the distance between their respective scalar components (Eq. 3) is smaller than \( r \). In step 3, we calculate the probability of the data point of \( X^m(j) \) that exists within the tolerance level of \( X^m(i) \) for each observation, \( 1 \leq i \leq N - m + 1 \). In other words, if the number of data points \( c_i^m(r) \) of \( X^m(j) \) series is similar to that of the \( X^m(i) \) series, the relative frequency to find a vector, \( X^m(j) \) within the tolerance level \( (r) \) of \( X^m(i) \) is obtained as

\[
c_i^m(r) = \frac{d_{i}^{m}(r)}{N-m+1},
\]

where \( c_i^m(r) \) reflects the extent of the gap between the two vectors:

\[
d [X^m(i), X^m(j)] \leq r, \quad \text{and} \quad 1 \leq j \leq N-m.
\]

Kristoufek and Vosvrda (2014) document \( c_i^m(r) \) as the measure of autocorrelation due to assessing the maximum distance between the lagged series. Next, we compute the average of natural logarithm of each \( c_i^m(r) \) during the \( i \) as follows:

\[
\psi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \ln[c_i^m(r)]
\]

We extend the embedding dimension to \( m+1 \), which takes the following form, and then compute the logarithmic average relative frequency of \( X^{m+1}(j) \) that remains similar to that of \( X^{m+1}(i) \) series within the tolerance level.

\[
\psi^{m+1}(r) = \frac{1}{N-m} \sum_{i=1}^{N-m-1} \ln[c_i^{m+1}(r)]
\]

Both the relative average frequency, \( \psi^m(r) \) and \( \psi^{m+1}(r) \) reflects the extent of similarity between \( X_i \) and \( X_j \) patterns within the specified tolerance level at different time dimensions (i.e., \( m \) and \( m+1 \)). Finally, we calculate the APEn for the financial time series by analyzing the relative magnitude between the repeated patterns as follows:

\[
\text{APEn}(m, r, N) = \psi^{m+1}(r) - \psi^{m+1}(r)
\]

The value of \( \text{APEn}(m, r, N) \) ranges between 0 and 2; 0 indicates the perfectly deterministic time series, and 2 denotes the presence of complete randomness of
the series. Therefore, the value of \( APEn \) around 0 suggests a perfectly repeatable pattern of returns with less complexity in the return series. Such patterns are thus predictable and allow the market participants to obtain abnormal profits. The value of \( APEn \) closer to 2 indicates a higher degree of irregularity in the financial markets, and thus the stock returns are unpredictable. In other words, the return series follows a random walk. Therefore, the computed entropy is a strong indicator of informational efficiency; higher entropy suggests the presence of a greater extent of randomness in the market returns and thereby a higher level of informational efficiency and vice versa.

The extent of market randomness varies from one stock market to other, which needs a better articulation of diversified features of informational efficiency. Further, the geographical discrepancies and diversified market structure may affect the characteristics of the market efficiency. Institutional investors have developed over the years several region-specific funds. The investors also perceive regions as homogenous entities in their investment decisions (Divecha et al. 1992; Kaminsky et al. 2001; Goyal 2016; Hiremath 2018). In this context, we carry out the \( k \)-means cluster analysis to capture the differences in the degree of informational efficiency in the entire sample as well as within each regional sub-sample. The region is not a cluster, but the cluster is that of efficient and inefficient markets. Such an analysis overcomes the bias of homogeneity among investors. This efficient formal inference procedure ensures the robustness of our findings:

\[
C_k = \sum_{x_i \in c_k} (x_i - \mu_k)^2
\]  

(8)

where \( C_k \) represents the \( k \)-mean clusters of the given series. We calculate \( C_k \) as the sum of squared distances between the data points \( (x_i) \) and the clustered centers or centroid \( (\mu_k) \). Hence, we apply three alternative algorithms – Elbow (Bholowalia & Kumar, 2014), Silhouette (Thinsungnoen et al. 2015), and Gap (Tibshirani et al. 2001) statistics to obtain the appropriate \( \mu_k \). We define the robust value of \( \mu_k \) as 2 based on all the methods (Fig. 10).

We collect the daily closing index prices of 87 stock markets from the Bloomberg Terminal from January 1, 1994, to August 3, 2017.\(^6\) The sample consists of 45 DMs and 42 EMs. The stock indices of each market consist of broad-based stocks. The index is considered as the representative index of each market. We calculate the logarithmic returns of stock indices to normalize the returns to avoid artifacts in estimating entropy values due to the sudden changes in stock prices. The formula for calculating stock returns \( (r_t) \) is as follows:

\[
r_t = \ln \left( \frac{p_t}{p_{t-1}} \right) \times 100
\]  

(9)

where \( p_t \) and \( p_{t-1} \) represent the current and past closing stock prices.

\(^6\) The beginning date of a few indices varies based on the availability of the data.
The descriptive statistics presented in Table 2 show that average returns of the markets are positive except Kuwait, Greece, Indonesia, Palestine, Serbia, Bosnia & Herzegovina, Ukraine, Kenya, Mexico, Argentina, Venezuela, Egypt, Turkey, Bangladesh, and Costa Rica. The skewness of the returns across the markets is mixed, whereas the Kurtosis statistics indicate a leptokurtic peak. Further, the significant Jarque–Bera test confirms the non-normal distribution of the stock returns series, whereas the unit-root test confirms the stationarity of the data series.

**Empirical Results**

We estimate the $APEn$ for the full sample and discuss the estimates. We also present a region-wise cluster analysis to decipher the relative efficiency across the geographical regions and types of markets. We also estimate the $APEn$ in a rolling window to show the time-varying efficiency and explain the evolution of markets using the adaptive market framework.

**Full-Sample Analysis**

We quantify the degree of randomness in the stock return series and rank the stock markets as per the level of absolute market efficiency (Table 1). Hence, our calculated $APEn$ estimates act as the proxy for the absolute informational efficiency of the respective markets. The methods applied in the extant literature assume noiseless data and thus fall short of examining complex patterns of high-dimensional systems. Mensi (2012) ranks the emerging stock markets based on Shannon entropy which produces biased estimates in the presence of the system noise and hence cannot effectively capture the AMH characteristics such as regional diversity, institutional heterogeneity, and diversified market conditions. Kristoufek and Vosvrda (2013, 2014) and Baciu (2014) employ the composite efficiency indices constructed by combining multiple methods such as long-range dependence, fractal dimensions, and entropy. $APEn$ approach efficiently ranks the markets in the presence of financial noise and complexities. Hence, this approach is suitable to address the current research problem. $APEn$ has an advantage over other methods in examining the time-varying patterns of the price complexities and, therefore, is considered an efficient indicator of financial market stability (Pincus and Kalman 2004). The approach further ensures the robustness of inferences (Sleigh and Donovan, 1999), which motivates us to rank the cross-regional stock markets solely based on their level of $APEn$ estimates.

Note: The table presents entropy values for each market computed for the full sample period. The markets with entropy values closer to 2 are highly efficient as returns exhibit a higher degree of complexities, whereas the entropy around zero indicates the predictability.

Japan is the most informationally efficient market, followed by Switzerland and Australia (Table 1). The unique and epoch-making financial market reforms such as the introduction of the off-hour trading system in 1997, implementation of the big
Table 1  Ranking of the stock markets

| Country   | Index     | APEn | Ranking | Country   | Index     | APEn | Ranking |
|-----------|-----------|------|---------|-----------|-----------|------|---------|
| Japan     | TPX       | 2.071| 1       | Colombia  | IGBC      | 1.877| 45      |
| Switzerland | SMI      | 2.055| 2       | SK        | KOSPI     | 1.871| 46      |
| Australia | ASX       | 2.054| 3       | Serbia    | BELEXLIN  | 1.869| 47      |
| Chile     | IPSA      | 2.047| 4       | Tunisia   | TUSISE    | 1.849| 48      |
| Brazil    | BVSP60    | 2.038| 5       | Croatia   | CRO       | 1.848| 49      |
| Spain     | IBEX35    | 2.034| 6       | Russia    | MCX       | 1.836| 50      |
| Portugal  | PSI-20    | 2.033| 7       | Jamaica   | JMSMX     | 1.835| 51      |
| Poland    | WIG20     | 2.032| 8       | B&H       | SASMX     | 1.819| 52      |
| France    | CAC40     | 2.031| 9       | Bahrain   | BB        | 1.801| 53      |
| Sweden    | OMXS30    | 2.029| 10      | Sri Lanka | CSE       | 1.798| 54      |
| Germany   | DAX       | 2.029| 11      | Macedonia | MBI       | 1.771| 55      |
| Denmark   | OMXC20    | 2.027| 12      | Kenya     | KNSMX     | 1.762| 56      |
| UK        | FTSE100   | 2.022| 13      | Slovakia  | SKSM      | 1.761| 57      |
| South Africa | FTSE/JSE | 2.017| 14      | UAE       | ADSMI     | 1.751| 58      |
| India     | Nifty50   | 2.007| 15      | Indonesia | JKSE      | 1.717| 59      |
| Taiwan    | TAIX      | 1.993| 16      | Bulgaria  | SOFIX     | 1.707| 60      |
| Netherlands | AEX     | 1.993| 17      | Iceland   | OCEXI     | 1.699| 61      |
| HK        | HSI       | 1.989| 18      | Ukraine   | PFTS      | 1.688| 62      |
| Luxemburg | Luxx      | 1.988| 19      | Bermuda   | BSX       | 1.687| 63      |
| Canada    | SPTSX     | 1.987| 20      | Nigeria   | NGSEINDEX| 1.683| 64      |
| New Zealand | NZX50  | 1.985| 21      | Romania   | BET       | 1.671| 65      |
| USA       | DJIA      | 1.984| 22      | Kuwait    | SECTMIND  | 1.668| 66      |
| Austria   | ATX       | 1.981| 23      | Lebanon   | BLOM      | 1.664| 67      |
| Malta     | MALTEX    | 1.978| 24      | Malaysia  | KLS       | 1.646| 68      |
| Hungary   | BUX       | 1.968| 25      | Bangladesh| CSE       | 1.633| 69      |
| Italy     | FTMIB     | 1.963| 26      | Cyprus    | CYSMARTPA | 1.633| 70      |
| Lithuania | VILSE     | 1.960| 27      | Mauritius | SEMTRI    | 1.624| 71      |
| Singapore | STI       | 1.958| 28      | China     | SSEC      | 1.621| 72      |
| Finland   | OMXH25    | 1.955| 29      | Kazakhstan| KZKAK     | 1.584| 73      |
| CR        | PX        | 1.953| 30      | SA        | TASI      | 1.560| 74      |
| Belgium   | BFX       | 1.952| 31      | Qatar     | DSM       | 1.509| 75      |
| Israel    | TA35      | 1.950| 32      | Tanzania  | DARSDESI  | 1.487| 76      |
| Estonia   | TALSE     | 1.948| 33      | Argentina | MERV      | 1.482| 77      |
| Thailand  | SETI      | 1.947| 34      | Oman      | MSM30     | 1.469| 78      |
| Norway    | OSEBX     | 1.945| 35      | Jordan    | JOSIGW    | 1.230| 79      |
| Philippines | PSI     | 1.942| 36      | Greece    | ASE       | 1.221| 80      |
| Ireland   | ISEQ20    | 1.937| 37      | Egypt     | EGX30     | 1.129| 81      |
| Morocco   | MOSEMD    | 1.932| 38      | Mongolia  | MSETOP    | 1.168| 82      |
| Turkey    | BIST      | 1.924| 39      | Venezuela | IBVC      | 0.941| 83      |
| Mexico    | MEXBOL    | 1.914| 40      | Panama    | BVPS      | 0.591| 84      |
| Slovenia  | SBITOP    | 1.913| 41      | Palestine | PASISI    | 0.387| 85      |
| Namibia   | NSEIL     | 1.906| 42      | Peru      | IGBVLVOL  | 0.160| 86      |
bang economic reforms in 1998, adoption of timely disclosure network and delivery versus payments (DVP) system in 1999, depreciation of the yen during 2011–13, and lower vulnerability to the external shocks made Japanese stock market as the most efficient one. In the case of Switzerland, the implementation of the Financial Market Supervision Act (FINMA) and the International Monetary Fund (IMF) grant of CHF 400 billion for the development of financial markets improve the weak form of efficiency. The sound macroeconomic and market fundamentals determine the efficiency level in Australia. Our result supports Kristoufek and Vosvrda (2013), who document Japan as the most efficient market between 2000 and 2011. Nonetheless, Cajueiro and Tabak (2005) and Lim (2007) find the highest level of efficiency in the US stock markets during 1991–2004 and 1992–2005, respectively. Mensi (2012) finds Argentine as the most efficient stock market based on Shannon entropy estimates. Our ranking differs from the previous research. We consider a relatively long period and cover the important events. Our method is also robust to financial instability and noise.

We follow the International Finance Corporation (IFC) method to classify the markets as DMs and EMs. We show that DMs secure the topmost positions in the efficiency ladder. The finding supports the view of Yang et al. (2019) with the analysis of the pricing part of the stock market efficiency. The disaggregated analysis of different market conditions implies the highest level of efficiency in Brazil, South Africa, and India among EMs. A higher degree of informational efficiency of these markets is associated with setting up the common currency reserve pool with the minimum capital of $100 billion reserves after the global financial crisis (GFC). This reserve plays a vital role in protecting these markets against further external financial shocks and funding the local market infrastructures. Moreover, 71 percent devaluation of the Brazilian real in 1999, the memorandum of the investment fund protocol of $120 million between the US and South Africa in 1996, and increased IPO activities in India during 2005 improved the efficiency of these markets.

A disaggregated analysis of geographical regions shows European stock markets as highly efficient compared to the other regions (Table 1). The adoption of a single

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Table 1 (continued)

| Country | Index | APEn  | Ranking | Country | Index | APEn  | Ranking |
|---------|-------|-------|---------|---------|-------|-------|---------|
| Latvia  | RIGSE | 1.901 | 43      | Costa Rica | CRSMBCT | 0.0002 | 87      |
| Pakistan | KSE   | 1.892 | 44      |         |       |       |         |

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7 Kristoufek and Vosvrda (2013) analyze the Japanese NIKKEI whereas we include Japanese Tokyo stock exchange as our sample market for the analysis. In this aspect, we argue that Japanese stock market remained the most efficient market over the years.

8 IFC, World Bank classifies the stock markets based on level of per capita gross national income (PGNI). Accordingly, the stock markets of the upper middle-income, lower middle income, and the lower-income economies having PGNI of below $12,235 are EMs whereas the stock markets of the higher income countries having PGNI of above $12,235 are considered as the developed markets.

9 We report the list of disaggregated markets in Appendix A.2.3.
currency system (Euro) reduced the exchange rate risks within the region, which made Europe a significant investment destination for international investors. The EMs in Asia and North–South America are the least efficient. The geopolitical tensions in these regions and the greater vulnerability of the markets to the regional crisis explain the lower degree of information aggregation. Our results on the ranking of regional stock market efficiency are in line with Kristoufek and Vosvrda (2013, 2014), who document the highest (lowest) efficient markets in Europe (Asia-Latin America) during 2000–2011. Our finding on the highest efficiency in Europe also supports the findings of Mensi (2012). These studies employ composite index and Shannon entropy, respectively.

The extent of variation in \( APEn \) values from one market to another motivates us to cluster the regional stock markets according to their level of efficiency (Eq. 8). The cluster analysis presented in Fig. 1 indicates a higher level of efficiency in the

![Figure 1](image-url)
Fig. 2 Cluster analysis of the stock markets in Asia. Note: Figure shows the absolute deviation of the stock markets in Asia from the level of predictability (Panel A1, B1, C1 for Asia, Asian DMs, and Asian EMs, respectively), and their ranking and clustering (in Panel A2, B2, C2 for Asia, Asian DMs and EMs respectively) based on the level of absolute efficiency. Panel A1 and A2 represent the ranking and clustering of the stock markets in Asia. Panel B1 and B2 shows the ranking and clustering within the sub-sample of Asian DMs, whereas Panel C1, C2 report ranking and cluster analysis within the EMs. The centers of the ranking plots (A1, B1, and C1) suggest the normal deterministic state. The higher deviation from the center suggests the presence of a higher degree of complexities in the particular market and thus suggests a higher level of informational efficiency, and vice versa. The cluster analysis (Panel A2, B2, C2) reports the benchmark entropy estimates for the higher or lower degree of informational efficiency in Asia along with in its disaggregated DMs and EMs. The threshold for the higher degree of efficiency in the aggregated sample (i.e., 1.3, shown in Panel A2) and regional DMs (i.e., 1.7 in Panel B2) remain the same as in the previous full-sample and full-DMs sub-sample analysis respectively (Fig. 1). Nevertheless, the EMs in Asia, unlike the full-EMs sample (Fig. 1), are highly efficient due to their higher APEn values of above 1.5.
sample stock markets except Greece, Jordan, Egypt, Mongolia, Venezuela, Panama, Palestine, Peru, and Costa Rica (Panel A). The market returns in DMs and EMs exhibit a higher degree of complexities (i.e., above 1.7 and 1 respectively) (Fig. 1, Panel B) and thus are highly efficient. Nevertheless, the degree of efficiency is lower in Slovakia, United Arab Emirates, Iceland, Bermuda, Kuwait, Cyprus, Saudi Arabia, Qatar, Oman, and Greece among the DMs, and Venezuela, Panama, Palestine, Peru, and Costa Rica among the EMs.

We further analyze the stock market efficiency based on geographical characteristics to ensure the robustness of ranking and inferences. Japan is the most efficient market in Asia, whereas Oman, Qatar, Saudi Arabia, Kuwait, and United Arab Emirates are the least efficient in the region (Fig. 2, Panel 3B1 and 3B2). The lack of reforms, the weak primary market in the Sultanate with only one IPO during 2010, and lower trading volume during 2015 explain the lower level of informational efficiency of these markets. The Asian Gulf markets, although economically developed, but these markets are not on par with free capital markets in the West. Among the Asian EMs, India is the most efficient (Fig. 2, Panel C1) because of its sustained economic reforms since 1991 and a tremendous investment in market infrastructure. Most of the stock returns in Asia hold a greater extent of complexities of above 1.5 except Jordan, Mongolia, and Palestine (Panel A2), indicating a random walk of returns.

In Europe, Switzerland and Greece experience the highest and lowest degree of efficiency, respectively. Our results support Baciu (2014), who ranked the European stock markets based on long-range dependence, fractal dimensions, and efficiency indices. The lowest deviated pattern from the central predictability point in Greece is associated with the internal sovereign debt crisis in 2011 and the twin deficit during 2015 (Fig. 3, Panel A1). Among EMs, Serbia is relatively efficient due to its upgraded credit ratings from BB− to BB+ and the sound macroeconomic fundamentals that attract major institutional investors. In contrast, the lack of financial market reforms and political instability reduces the level of efficiency of the Romanian stock market (Fig. 3, Panel C1). We find a higher degree of complexities in most of the European stock markets (Panel A2) except Slovakia, Ireland, Cyprus, and Greece among the DMs group (B2); and Bulgaria, Ukraine, and Romania among the EMs peers (C2).

Canada and Chile are the most efficient markets (Fig. 4 Panel A1). Such a highest level of efficiency is associated with increased international competitiveness during the free trade reforms. Further, the sound macroeconomic fundamentals insulated the economies from external shocks. The disaggregated analysis reveals Bermuda’s bottom-most position among the DMs due to its relatively more significant exposure to external shocks. In EMs, Brazil holds the highest level of efficiency, whereas North-American Costa Rica remains inefficient as the market is still in its infant stage (Panel C1). All the stock markets of the region exhibit random-walk characteristics (i.e., entropy value ≥ 1.5), barring Venezuela, Panama, and Costa Rica (A2 and C2).

In the African and Pacific Ocean regions (Fig. 5), Australia and South Africa exhibit the highest degree of complexities among DMs and EMs, whereas Peru

10 We arrange the stock markets from Africa, and Pacific Ocean in one sample due to insufficient number of markets for a meaningful cluster analysis.
exhibits predictable patterns. We refute the previous findings of Mensi (2012) that suggested the lowest degree of efficiency in South Africa during 1997–2007. These markets have introduced several reforms in recent years, which positively impact the stock market efficiency. Further, the approximate entropy has the advantage over other methods in capturing the complexities. The previous research predominantly termed the developing markets inefficient and thus failed to capture the impact of liberalization. Our present findings show that the rejection was due to complexities which the previous methods applied were not appropriate to capture.

The degree of informational efficiency and its characteristics varies from region to region and from one type of market to the other. We show that the geopolitical, geo-economic, and development stages of the economy & the market describe the variation in the degree of efficiency. Hence, investigation of the evolution of these markets is indispensable for a comprehensive understanding of the level of efficiency.

**Rolling Window Analysis**

We employ the rolling window approach to measure the degree of time-varying efficiency. This approach overcomes the problem of an arbitrary division of the full sample into various subsamples, which are often biased (Campbell et al. 1997). The pre and post-analysis or a structural break approach do not capture the impact of any event, policy, or regulatory change over the period. Static analysis cannot capture such continuous changes. The event study analysis is often biased because of their sensitiveness to the event date and other biases in financial market research (Campbell et al. 1997). Therefore, the rolling window framework is appropriate for investigating the time-varying efficiency and identifying the events associated with such time variation. In the rolling window analysis, the selection of the length of the window size remained controversial (Zhou and Lee, 2013; Charles et al. 2012). Hiremath and Narayan (2016) suggest that the length of the window size should have enough observations to capture the size and power properties of the time series methods. Therefore, we choose an optimal window length of 500 time-series
observations following the approach of Inoue and Rossi (2017). This method minimizes the quadratic loss function and performs excellently under structural changes. Besides, the method is asymptotically valid. Our sample is rolled one point forward by eliminating the first observation and including the next one to estimate the next entropy value.

The descriptive statistics in Table 3 show that the average degree of entropy $\geq 1$ for all stock markets (except Palestine, Panama, and Peru). The estimate suggests the randomness of returns and therefore exhibits a higher level of informational efficiency. The positive skewness of the entropy series for most DMs suggests a
greater magnitude of unpredictability and, thus, a higher degree of efficiency. In EMs, negative skewness of the entropy values suggests that most of these markets are characterized by a lower degree of efficiency due to their peculiar characteristics. Nevertheless, the returns pattern of the EMs such as India, Philippines, Sri-Lanka, Thailand, Croatia, Serbia, Ukraine, Italy, Kenya, South Africa, Tanzania, Tunisia, Mexico, Brazil, Russia, and Turkey display remarkable improvement in the degree of informational efficiency but not identical to the DMs. The kurtosis of the entropy values with a few exceptions suggests the platykurtic statistical distribution and, therefore, distraction is flat, and the tail is thick. Jarque–Bera statistics also reject normal distribution (Table 3).

We present the rolling entropy estimates across the regions in Figs. 6, 7, 8, 9. We observe the evolution of the level of informational efficiency over the period, and markets switch between efficiency and predictability. This transition from episodes of efficiency-predictability is neither smooth nor fixed. It shows that the market continuously changes, and thus challenging for an investor to earn excess returns despite potential opportunities. We inquire into the economic and non-economic events attributed to episodic stock market efficiency. Therefore, we broadly survey the annual reports of the respective country’s monetary authority, newspapers, economic and financial surveys of the IMF and the credit rating agencies. Besides, we identify certain region-specific events associated with the time variation in each region.

We find three common periods 1995–96, 1999, and 2014 during which informational efficiency across the markets increased, indicating the influence of universal and global events on efficiency. The economic reforms and consequent sound macroeconomic fundamentals are associated with these peaks. We find that the changes in microstructure and improvement in trading infrastructure boosted the efficient functioning of the stock markets. In particular, the electronic trading platform enables the investors to update with the new information, and their trading quickly incorporates the information into the security prices. Besides, the sound macroeconomic fundamentals attracted major institutional investors, which enriched the domestic stock markets with global information (Bae et al. 2012). Nevertheless, Israel, Oman, South Korea, Chile, and Jamaica could not benefit from global influence because
of their domestic political instability and deterioration in macroeconomic situations. Further, the local financial crashes restrained Taiwan, Sri Lanka, Mexico, Argentina, the US, Peru, Jordan, Kuwait, Philippines, Lebanon, and Portugal from taking advantage of the conducive global environment.

The stock market efficiency faced the trough periods in 1997–98, 2000–01, 2004–05, 2007–08, 2010–12, and 2015–16. Several financial shocks such as the East-Asian currency crisis, the US dot-com bubble burst, and a terrorist attack on
World Trade Center, the US-Iraq war, dollar crisis, global financial crisis (GFC), Eurozone sovereign debt crisis, and fluctuation of international oil prices are associated with the respective international troughs. Nonetheless, some markets with better market characteristics, advanced trading infrastructure, and an improved macroeconomic environment defy such global downtrends and hold better diversification opportunities for international investors. For instance, Japan was immune to the major downturns in the global markets thanks to its unique big-bang reforms. The creation of Euronext\(^{11}\) positively influenced the informational efficiency of France and the Netherland between 1997 and 2005 and therefore held better returns for both the US and Asian investors.\(^{12}\) With their limited degree of financial openness, Kenya, Lithuania, and Sri Lanka remain immune to the significant troughs. These economies can be benefitted from liberalization, and global investors need to explore them for better investment and diversification opportunities. Philippines, Kazakhstan, Mongolia, Austria, Slovakia, Latvia, Poland, Ukraine, Jamaica, Colombo, Tunisia, Egypt, Lebanon withstood the dot-com bubble burst, and Palestine, Bangladesh, and Morocco remained unaffected by the GFC. These countries still maintain extensive capital controls.

\(^{11}\) Euronext is a group of financial markets from France, Belgium, and the Netherland. The cooperation mechanism of Euronext monitors and supports the integration of operational systems for trading, clearing, and settlement-delivery and strives for harmonization and the unification of the market rules.

\(^{12}\) We argue that the lack of integration of the Euronext with the US and Asia makes the former region immune to the particular shocks and therefore indicate the better diversification opportunities for investors from the latter regions.
Region-Specific Events

We estimate time-varying efficiency across the regions and identify the periods during which each region exhibits a unique pattern in the degree of stock market efficiency. We decipher the region-specific economic and non-economic events explaining the ups and downs of the stock market efficiency in the region. Such events ostensibly vary from one region to another. We measure the extent
of time-varying efficiency in Asia (Fig. 6). We do not find common peaks and troughs in the stock markets of Asia. The evidence suggests the absence of market convergence, and thus functioning of each market depends on its unique characteristics in Asia. Such a feature implies the possibility of diversification opportunities.
within the region. Simultaneously, the more significant capital inflows from the global market boosted the trading & market turnover and increased the informational efficiency in Hong Kong, United Arab Emirates, Indonesia, India, Philippines, Pakistan, Malaysia, Palestine, Lebanon, and Bangladesh (see, Hiremath and Kattuman 2017). The peaks in South Korea and Thailand (1998), Pakistan (2016);
Jordan (2002–04); and Mongolia (2017) are associated with the IMF grants for domestic financial stability. The increased degree of efficiency in Taiwan and the Philippines (2014); Singapore, Saudi Arabia, and Pakistan (2003–04); Malaysia (2006); and Japan (2017) are attributed to the heightened corporate earnings.

Fig. 9 Evolution of stock market efficiency in Africa, and the Pacific Ocean. Note: The sample consists of 2 DMs and 9 EMs. The red lines explain the trends in the entropy estimates for the DMs of the Pacific Ocean, and blue lines display that of the African EMs over the period.
However, due to economic instability, Mongolia, the Philippines, Sri-Lanka, Thailand, and Jordan do not follow such a common uptrend.

We find the local geopolitical tensions as a common factor associated with the downturns in Israel, South Korea, Taiwan, and Jordan (2002); Kuwait, and Singapore (2016); Philippines and Malaysia (2010); Lebanon and Thailand (2014); Kazakhstan and Bangladesh (2015); Sri Lanka (1994); and Mongolia (2005). In 2015, the troughs in the degree of efficiency in Hong Kong, Taiwan, Qatar, and Malaysia were associated with the significant sell-offs by institutional investors. A similar plunge in Japan, Taiwan, the Philippines, and Thailand was related to the spillover effect of China's financial turbulence. The Syrian conflicts in the Middle East are another region-specific factor associated with the deterioration of informational efficiency in a few markets such as Jordan, the Philippines, Kuwait, and Lebanon.

Additionally, the higher interest rate environment indicates the increase in macro stress that adversely affected the level of informational efficiency in Malaysia and the Philippines (2006), Israel and Hong Kong (1999), Qatar (2000), and Japan (2013). Overall, most of the stock markets in Asia parade the bearish market sentiments due to the Asian currency crisis and the consequent contagion effects across the regions, which ruffle domestic investors’ confidence, thus reducing the informational efficiency in the region. Nevertheless, Oman, Japan, South Korea, and China resisted this downtrend thanks to their structural reforms.

In Fig. 7, we present the degree of time-variation in the stock market efficiency in the European continent. We find 2002–04, 2004–05, 2005–06, and 2014–15 as the episodes of the higher level of efficiency in Europe. The adoption of the single currency system led to the unification of the regional financial markets and therefore removed the exchange rate risk within the region. In addition, the successful launching of SETSTM and landmark™ in the UK, new amendment for the listing of securities in France, and implementation of the Single Match System by Swift Net in Spain on the eve of the common currency platform efficiently increased the speed of information dissemination into the security prices. However, Cyprus, Slovakia, Slovenia, Croatia, and Malta lag behind due to their delay in joining the Euro system. The efficiency of European stock markets is also associated with the local corporate reforms, such as the increase in mergers and take-over bids in the major European stock markets.

The degree of stock market efficiency in Europe hit a record low during 2012–13 and 2015–16. The double-dip recession due to the Eurozone sovereign debt crisis and the vulnerability of the regional markets to the Brexit negotiation can be attributed to such informational inefficiency. Nevertheless, the policy measures in France, Denmark, Iceland, Norway, Belgium, Czech Republic, Hungary, Slovenia, and Bosnia & Herzegovina insulated the efficiency of these markets from the crisis. Similarly, Switzerland, Netherland, Ireland, Ukraine, Serbia, and Romania were not affected by the news around Brexit and thus provided stability to the markets.

We document a higher degree of efficiency in North–South America in 2003–04, which was better than many other regions (Fig. 8). The stock markets of the North-American region predominantly imitate the US market. Nonetheless, episodes of inefficiency during 1994–95 and 1998–2002 were due to Mexico’s peso crisis and the great depression in Argentina. Besides, the Petroleum crisis in Brazil and domestic political instability in Canada adversely affected the level of informational efficiency of these markets.
We find no significant common episodes of varying efficiency in Africa and the Pacific Ocean region (Fig. 9). However, we find the sizeable foreign institutional investors as the primary factor associated with a higher level of efficiency in South Africa, Peru, Nigeria, Mauritius, Tanzania, and Morocco. The global investors incorporate global information into the domestic stock markets, internationalize the local companies, and thereby increase the level of informational efficiency in the region. Nevertheless, a few markets such as Kenya, Namibia, and Tunisia failed to benefit from such investment due to their below-average market infrastructure and weak economic growth. In contrast, domestic financial instability and lower economic growth are the common factors related to the periods of inefficiency in Africa. The markets in the Pacific Ocean follow the global trends alone and exhibit no unique episodes.

We further compute the rolling entropy estimates for the cross-regional stock markets in 100, 150, 300 random sequences (11–16) to ensure robustness to our inferences. We compute Kruskal–Wallis statistics to compare the extent of time-variation in the degree of informational efficiency of DMs and EMs.13 The Kruskal–Wallis non-parametric statistics show the significance of differences in the entropy estimates in different window periods. The rejection of null indicates that the values of the entropy estimates differ from one window to another. In other words, the result implies a time-dependent pattern in the degree of complexities of the return series.

We show that economic reforms, capital market liberalization combined with microstructure changes significantly boosted the level of efficiency in EMs. Nonetheless, financial liberalization also exposed these economies to external shocks. The EMs that pursued constant and gradual structural reforms, along with prudential norms such as stringent disclosure norms, higher corporate governance, effective regulation in place, have benefitted mainly from global finance without its ill-effects to a greater extent.

The findings suggest that EMs such as Africa were rarely affected by external factors because of a lack of economic liberalization and exposure to the global markets. However, these markets lost the benefits of liberalization in terms of vibrancy and informational efficiency, as the evidence suggests the lowest degree of efficiency. The Asian markets not only defy the global trends often but rarely move in tandem with each other, especially after 1997. The evidence suggests that these markets possibly offer diversification opportunities. The result suggests that investors adapt to the changing market environment, which results from various factors. As investors learn and adapt to the market ecology, the market moves towards efficiency. However, investors take time to respond to changes in regulations, external or internal shocks, trading mechanisms, among others. Due to such delay, returns do not adjust instantaneously to the new information and allow smart traders to find potential excess returns as they quickly adapt to changing market ecology. The previous literature termed developing and emerging markets inefficient due to the presence of predictability.

Nevertheless, the complexity of the return behavior, as evident from the entropy estimates in the present study, suggests that the excess returns, although present, are not easily exploited by smart and rational traders. Hence, the developing and emerging markets have improved the degree of efficiency by introducing reforms. The returns behavior in these markets is complex. Our results thus do not rule out the

13 We have not reported these test statistics to save the space.
technical analysis. The technical analysts need to identify these cycles of efficiency and inefficiency and quickly adapt to outsmart the market. The finding of the evolutionary nature of market efficiency and the influence of varied factors and events for such evolution validate the AMH framework reconciling the EMH and its anomalies. The entropy method applied in this study is proved to be appropriate to capture such complexities and evolving market ecology.

Conclusion

The present study measures the absolute and evolving efficiency of the stock markets across Asia, Europe, North–South America, Africa, Pacific Ocean regions. We rank the stock markets based on their level of informational efficiency using the entropy method and find Japan, Switzerland, and Australia as the most efficient markets. The analysis shows that European markets are the most efficient markets. The degree of efficiency of the developed stock markets is higher irrespective of geographical location. The emerging stock markets have significantly improved their level of efficiency by introducing economic reforms and market microstructure changes. However, the evidence shows that growing globalization exposed them to global shocks, and the stock market efficiency hit a low at times due to external shocks. The findings of the study suggest that stock market efficiency evolves over the period. The global, regional, and local economic and non-economic events influence such evolution. The AMH framework better describes such evolution and factors.

We show that abnormal returns often exist in the markets, but such opportunities are time-varying and complex. The finding suggests that traders need to quickly adapt and innovate in order to earn excess returns. The traders require to identify the episodes of predictability and follow a smart investment strategy since such opportunities stay for long. In such a case, active portfolio management assumes further significance. Our evidence does not rule out the importance of technical trading as episodes of predictability arise in the market from time to time. However, technical analysts need to adapt quickly in a competitive market and under complex returns to make abnormal profits. The findings of the present study suggest that global investors should avoid homogeneity bias about a geographical region or type of market as abnormal returns are present within each region at different times and across markets within the region. Diversification and higher return opportunities exist within the region as well as the same type of markets. Africa can take clues from the policy experience of the markets in Asia to make better use of liberalization. Our inference is limited to the chosen statistical models. The further verification of portfolios can be exciting but beyond the scope of the present work. The present research needs to be extended into a technical trading framework to verify profitability. Also, testing portfolio opportunities based on the present evidence can be part of future research.

Appendix A

See Tables 2, 3 and Figs. 10, 11, 12, 13, 14, 15, 16.
| Country       | Mean | S.D  | Skew | Kurto | JB Test | Obs | ADF Test | | Country       | Mean | S.D  | Skew | Kurto | JB Test | Obs | ADF Test |
|--------------|------|------|------|-------|---------|-----|---------|
| Israel       | 0.01 | 1.67 | -0.68| 10.85 | 62,900***| 6154| -17.53**| | India        | 0.03 | 1.75 | -0.18| 10.19 | 13,323***| 6154| -17.27* |
| HK           | 0.03 | 1.74 | 0.43 | 16.06 | 43,956***| 6154| -17.22**| | China        | 0.24 | 3.39 | 5.33 | 66.96 | 107,820***| 6154| -16.00** |
| Bahrain      | 0.02 | 0.69 | -0.06| 8.92  | 11,342***| 3413| -13.73**| | Indonesia    | -0.04| 2.69 | -1.65| 54.70 | 688,260***| 6154| -15.27** |
| Japan        | 0.03 | 1.51 | 0.12 | 7.05  | 4233*** | 6154| -17.36**| | Kyrgyzstan   | 0.04 | 2.86 | 0.76 | 51.12 | 485,610***| 4451| -15.02** |
| Kuwait       | -0.01| 1.15 | -0.61| 8.94  | 9600.1***| 2819| -11.59**| | Lebanon      | 0.02 | 1.29 | 3.79 | 65.48 | 101,810***| 5618| -16.59** |
| Oman         | 0.09 | 1.45 | 5.75 | 113.2 | 314,870***| 6154| -17.25**| | Malaysia     | 0.04 | 2.12 | 12.09| 351.6 | 313,180***| 6154| -17.81** |
| Qatar        | 0.07 | 1.88 | -0.76| 21.18 | 93,186***| 4953| -16.45**| | Mongolia     | 0.34 | 7.16 | 8.34 | 145.7 | 417,380***| 4848| -15.68** |
| Saudi Arabia | 0.12 | 1.87 | -0.91| 24.30 | 151,950***| 6134| -16.91**| | Pakistan     | 0.03 | 1.70 | -0.43| 10.71 | 15,464*** | 6154| -15.96** |
| Singapore    | 0.02 | 1.28 | -0.19| 4.74  | 4423.1***| 4677| -15.55**| | Palestine    | -1.51| 13.58 | 10.15| 113.1 | 287,870***| 5227| -10.78** |
| South Korea  | 0.04 | 2.38 | -0.02| 25.55 | 130,420***| 6154| -17.07**| | Philipines   | 0.04 | 1.83 | 1.85 | 37.18 | 303,350***| 6154| -16.95** |
| Taiwan       | 0.02 | 1.66 | -0.05| 7.40  | 4972.6***| 6154| -16.43**| | Sri Lanka    | 0.02 | 1.24 | 0.04 | 27.90 | 159,030***| 6154| -16.03** |
| UAE          | 0.07 | 1.24 | 0.31 | 8.42  | 12,312***| 4134| -13.91**| | Thailand     | 0.01 | 1.85 | 0.04 | 11.29 | 17,628*** | 6154| -15.37** |
| CR           | 0.05 | 1.80 | 0.71 | 12.14 | 37,961***| 6086| -16.78**| | Jordan       | 0.06 | 3.28 | -0.69| 58.89 | 801,660***| 6154| -22.43** |
| Denmark      | 0.05 | 1.42 | -0.26| 9.33  | 10,351***| 6154| -17.10**| | Bulgaria     | 0.13 | 2.27 | 6.05 | 112.6 | 234,350***| 4377| -13.79** |
| Estonia      | 0.07 | 1.32 | -0.35| 10.32 | 10,947***| 4848| -14.66**| | Croatia      | 0.02 | 1.49 | 0.23 | 12.66 | 26,478*** | 4377| -13.08** |
| Finland      | 0.04 | 1.71 | -0.07| 7.21  | 3595,6***| 4848| -15.72**| | Macedonia    | 0.02 | 1.54 | -0.62| 10.86 | 16,401*** | 3283| -11.36** |
| France       | 0.03 | 1.54 | 0.03 | 8.78  | 8580.9***| 6154| -17.84**| | Serbia       | -0.01| 1.35 | 0.07 | 14.65 | 30,001*** | 3283| -11.36** |
| Germany      | 0.05 | 1.59 | -0.08| 7.43  | 5059.3***| 6154| -18.14**| | B&H         | -0.03| 1.43 | 0.05 | 5.35  | 3585.6*** | 2998| -12.28** |
| Austria      | 0.03 | 1.59 | -0.20| 9.83  | 12,012***| 6154| -16.55**| | Ukranine     | -0.03| 2.85 | 0.32 | 29.48 | 185,110***| 5103| -14.96** |
| Greece       | -0.33| 6.85 | -16.44| 312.4 | 248,310***| 6154| -13.05**| | Italy        | 0.09 | 1.72 | -0.19| 8.58  | 632.7***  | 4848| -15.05** |
| Hungary      | 0.02 | 2.20 | -1.59| 30.43 | 195,630***| 6154| -16.33**| | Kenya        | -0.01| 1.47 | 1.56 | 93.44 | 210,020***| 6154| -17.41** |
| Ireland      | 0.02 | 1.57 | -0.52| 10.99 | 13,142***| 4848| -16.22**| | Mauritius    | 0.04 | 1.04 | -0.21| 8.29  | 10,208*** | 3543| -12.66** |
| Latvia       | 0.06 | 1.61 | -0.26| 11.32 | 24,602***| 4588| -15.59**| | Morocco      | 0.03 | 1.01 | -0.01| 4.22  | 302,45*** | 4066| -15.18** |
| Lithuania    | 0.05 | 1.27 | -0.65| 11.47 | 25,497***| 4587| -12.77**| | Namibia      | 0.03 | 2.19 | -0.22| 4.31  | 277,89*** | 3529| -14.73** |
| Luxemborg    | 0.01 | 1.54 | -0.23| 9.13  | 7643.2***| 4848| -14.78**| | Nigeria      | 0.02 | 1.91 | -1.29| 28.72 | 135,080***| 4848| -16.61** |

Panel A: Developed markets (DMs)
Panel B: Emerging markets (EMs)
| Country       | Mean | S.D  | Skew | Kurto   | JB Test | Obs  | ADF Test | Country       | Mean | S.D  | Skew | Kurto   | JB Test | Obs  | ADF Test |
|--------------|------|------|------|---------|---------|------|----------|--------------|------|------|------|---------|---------|------|----------|
| Malta        | 0.03 | 1.10 | -0.43| 23.60   | 85,893 * | 4848 | -16.71 **| Romania      | 0.07 | 3.07 | 0.61 | 35.87   | 278,560***| 5183 | -14.65 **|
| Netherland   | 0.02 | 1.49 | -0.13| 9.79    | 11,869 ***| 6154 | -17.59 **| South-Africa | 0.03 | 1.82 | -0.39| 5.76    | 8152.2 ***| 5764 | -17.81 **|
| Norway       | 0.06 | 1.84 | -0.28| 7.20    | 12,254 ***| 5632 | -16.71 **| Tanzania     | 0.06 | 1.34 | 1.96 | 39.80   | 186,070 ***| 2787 | -15.48 **|
| Belgium      | 0.01 | 1.42 | -0.12| 8.17    | 5423.7 ***| 4848 | -16.26 **| Tunisia      | 0.04 | 1.09 | 1.16 | 25.35   | 129,170 ***| 4777 | -14.76 **|
| Poland       | 0.02 | 2.15 | -0.11| 4.02    | 4052.1 ***| 6043 | -17.37 **| Peru         | 0.24 | 27.42| 2.50 | 583.9   | 865,420 ***| 6154 | -18.52 **|
| Portugal     | 0.01 | 1.37 | -0.18| 8.85    | 8837.3 ***| 6154 | -16.64 **| Jamaica      | 0.04 | 1.37 | 0.78 | 13.10   | 26,804 *** | 6154 | -16.96 **|
| Slovakia     | 0.12 | 2.30 | 4.12 | 53.72   | 596,710 ***| 4844 | -15.15 **| Mexico       | -0.05| 2.28 | -2.03| 23.87   | 150,240 ***| 6141 | -14.09 **|
| Slovenia     | 0.01 | 1.33 | -0.82| 11.81   | 22,230 ***| 3742 | -12.59 **| Panama       | 0.24 | 3.06 | 0.68 | 34.78   | 151,950 ***| 6134 | -16.91 **|
| Spain        | 0.04 | 1.62 | -0.09| 9.15    | 9728.6 ***| 6154 | -17.07 **| Argentina    | -0.15| 5.59 | -21.7| 612.2   | 956,660 ***| 6154 | -16.15 **|
| Sweden       | 0.03 | 1.77 | -0.02| 8.35    | 7340.3 ***| 6154 | -18.05 **| Brazil       | 0.04 | 2.72 | -0.09| 8.57    | 7988.3 *** | 6154 | -17.11 **|
| Switzerland  | 0.03 | 1.24 | -0.01| 7.21    | 4549.1 ***| 6154 | -18.62 **| Colombia     | 0.05 | 1.75 | -0.17| 8.47    | 12,608 ***  | 4197 | -14.28 **|
| UK           | 0.01 | 1.32 | -0.09| 11.48   | 18,538 ***| 6148 | -18.75 **| Venezuela    | -0.15| 7.41 | -14.4| 287.3   | 2,094,400 **| 6154 | -17.07 **|
| Canada       | 0.03 | 1.35 | 0.02 | 20.18   | 75,722 ***| 6154 | -18.06 **| Egypt        | -0.47| 6.63 | -10.93| 136.0   | 404,520 *** | 5109 | -12.48 **|
| Bermuda      | 0.03 | 1.39 | -1.07| 41.81   | 441,170 ***| 6035 | -14.61 **| Russia       | 0.06 | 3.22 | 0.26 | 13.83   | 41,404 *** | 5183 | -16.31 **|
| USA          | 0.02 | 1.15 | -0.51| 13.99   | 31,245 ***| 6154 | -18.44 **| Turkey       | -0.06| 3.45 | -1.37| 17.70   | 57,342 *** | 6154 | -17.03 **|
| Chile        | 0.02 | 1.37 | -0.35| 11.18   | 17,310 ***| 6154 | -16.59 **| Bangladesh   | 0.16 | 1.87 | 1.32 | 24.01   | 79,976 ***  | 3284 | -13.93 **|
| Australia    | 0.03 | 1.37 | -0.67| 11.88   | 20,718 ***| 6154 | -17.84 **| Costa Rica   | -0.005| 0.07 | -0.01| 0.03    | 340,950 *** | 6127 | 0.68 * |
| NewZea       | 0.06 | 1.23 | -0.59| 10.55   | 20,361 ***| 4326 | -14.95 **|
| Iceland      | 0.02 | 2.06 | -32.31| 18.09   | 837,930 ***| 6154 | -15.24 **|
| Cyprus       | 0.08 | 2.82 | 1.46 | 15.51   | 35,043 ***| 3369 | -13.59 **|

Note: Panel A reports the descriptive statistics of the stock returns from the DMs, whereas Panel B presents the descriptive statistics of the EM returns. We follow IFC to classify the sample markets into DMs and EMs based on the level of per capita gross national income (PGNI). SD denotes the standard deviation, and JB indicates the Jarque–Bera normality test. Skew and Kurto are skewness and kurtosis, respectively. Augmented Dickey-Fuller (ADF) test the null of unit root and rejection indicate stationarity of the market returns. *** and ** denote significance at 1% and 5% level, respectively.
| Country          | Mean  | S.D  | Skew | Kurto | JB Test | Obs | Country       | Mean  | S.D  | Skew | Kurto | JB Test | Obs |
|------------------|-------|------|------|-------|---------|-----|--------------|-------|------|------|-------|---------|-----|
| **Israel**       | 1.18  | 0.04 | 0.02 | −0.78 | 145.8***| 5655| **India**    | 1.17  | 0.04 | 0.25 | −0.51 | 123.08***| 5655|
| **HK**           | 1.18  | 0.05 | 0.70 | 0.26  | 489.9***| 5655| **China**    | 1.20  | 0.08 | −0.22 | −0.06 | 50.66***| 5655|
| **Bahrain**      | 1.17  | 0.02 | 0.56 | 0.07  | 155.5***| 2914| **Indonesia**| 1.17  | 0.08 | −2.60 | 8.90  | 25.059***| 5655|
| **Japan**        | 1.18  | 0.03 | 0.44 | −0.20 | 195.8***| 5655| **Khazakhstan**| 1.10  | 0.17 | −1.42 | 0.85  | 1460.1***| 5932|
| **Kuwait**       | 1.20  | 0.04 | −0.55 | −0.84 | 187.56***| 2320| **Lebanon**  | 1.16  | 0.07 | −0.55 | −0.50 | 317.05***| 5119|
| **Oman**         | 1.12  | 0.07 | −0.74 | 0.66  | 627.9***| 5655| **Malaysia** | 1.17  | 0.06 | −2.55 | 12.41 | 42.506***| 5655|
| **Qatar**        | 1.11  | 0.14 | −1.81 | 3.01  | 4134.4***| 4454| **Mongolia** | 1.10  | 0.18 | −1.83 | 2.25  | 3371.9***| 4349|
| **Saudi Arabia** | 1.18  | 0.06 | −0.59 | −0.16 | 340.28***| 5655| **Pakistan** | 1.16  | 0.03 | −0.04 | −0.04 | 12.49***| 5655|
| **Singapore**    | 1.15  | 0.02 | 0.03 | −0.02 | 5.81*   | 4178| **Palestine**| 0.98  | 0.31 | −1.74 | 1.66  | 2948.5***| 4728|
| **South Korea**  | 1.18  | 0.05 | 0.73 | 0.09  | 511.1***| 5655| **Phillipines**| 1.20  | 0.07 | 0.36  | −0.91 | 318.1***| 5655|
| **Taiwan**       | 1.17  | 0.04 | 1.32 | 2.33  | 2939.8** | 5655| **Sri Lanka**| 1.19  | 0.03 | 0.64  | 0.04  | 387.48**| 5655|
| **UAE**          | 1.17  | 0.04 | −0.35 | 0.05  | 79.02*** | 3635| **Thailand** | 1.18  | 0.04 | 0.40  | −0.17 | 164.19***| 5655|
| **Czech Rep**    | 1.16  | 0.04 | 0.92 | 1.21  | 1147.7***| 5587| **Jordan**   | 1.02  | 0.20 | −0.71 | −0.85 | 653.46***| 5655|
| **Denmark**      | 1.16  | 0.04 | 0.03 | −0.81 | 157.1*** | 5655| **Bulgaria** | 1.18  | 0.02 | −0.26 | −0.01 | 45.59***  | 3878 |
| **Estonia**      | 1.18  | 0.03 | 0.64 | −0.32 | 322.2*** | 4349| **Croatia**  | 1.18  | 0.04 | 1.35  | 1.13  | 1234.7***| 3450 |
| **Finland**      | 1.14  | 0.04 | 0.22 | −0.57 | 96.49*** | 4349| **Macedonia**| 1.18  | 0.02 | −0.05 | −0.50 | 31.17***  | 2785 |
| **France**       | 1.15  | 0.03 | 0.67 | 0.42  | 472.0*** | 5655| **Serbia**   | 1.20  | 0.07 | 0.44  | 0.37  | 107.2***  | 2850 |
| **Germany**      | 1.14  | 0.03 | 0.23 | −0.49 | 107.2*** | 5655| **B&H**      | 1.15  | 0.02 | −0.17 | 0.04  | 13.03***  | 2499 |
| **Austria**      | 1.15  | 0.03 | 0.51 | 0.29  | 268.6*** | 5655| **Ukraine**  | 1.17  | 0.05 | 0.38  | −0.25 | 124.75***  | 4604 |
| **Greece**       | 1.10  | 0.22 | −2.82 | 6.36  | 170.6*** | 5655| **Italy**    | 1.16  | 0.03 | 0.12  | −0.59 | 75.84***  | 4349 |
| **Hungary**      | 1.18  | 0.03 | 0.12 | 0.10  | 17.35*** | 5652| **Kenya**    | 1.21  | 0.06 | 0.12  | −0.23 | 26.29***  | 5655 |
| **Ireland**      | 1.15  | 0.04 | 0.27 | −0.55 | 109.5*** | 4349| **Mauritius**| 1.18  | 0.03 | −0.31 | −0.60 | 97.29***  | 3044 |
| **Latvia**       | 1.18  | 0.04 | 0.48 | −0.48 | 198.24** | 4089| **Morocco**  | 1.16  | 0.02 | −0.26 | 0.44  | 73.12***  | 3567 |
| Country     | Mean  | S.D   | Skew | Kurtto | JB Test | Obs | Country     | Mean  | S.D   | Skew | Kurtto | JB Test | Obs |
|-------------|-------|-------|------|--------|---------|-----|-------------|-------|-------|------|--------|---------|-----|
| Lithuania   | 1.18  | 0.04  | 1.34 | 1.27   | 1508*** | 4089| Namibia     | 1.13  | 0.02  | -0.09| -0.25  | 13.37*** | 3030|
| Luxemborg   | 1.16  | 0.05  | 0.55 | -0.61  | 293.2*** | 4349| Nigeria     | 1.16  | 0.04  | -0.40| -0.49  | 161.65***| 4349|
| Malta       | 1.17  | 0.04  | 1.56 | 2.21   | 2661.8** | 4349| Romania     | 1.23  | 0.05  | -0.90| 0.82   | 767.35** | 4684|
| Netherland  | 1.15  | 0.03  | 0.36 | 0.10   | 125.2*** | 5655| SAf         | 1.16  | 0.03  | 0.66 | 0.01   | 385.27** | 5265|
| Norway      | 1.17  | 0.03  | 0.23 | -0.48  | 98.69*** | 5133| Tanzania    | 1.18  | 0.06  | 0.08 | -0.95  | 89.17*** | 2288|
| Belgium     | 1.15  | 0.03  | -0.40| 0.14   | 122.5*** | 4349| Tunisia     | 1.21  | 0.05  | 0.75 | -0.31  | 425.67** | 4278|
| Poland      | 1.14  | 0.03  | -0.54| -0.22  | 290.3*** | 5544| Peru        | 0.78  | 0.53  | -0.36| -1.70  | 805.75** | 5655|
| Portugal    | 1.16  | 0.04  | 0.43 | -0.55  | 256.1*** | 5655| Jamaica     | 1.18  | 0.05  | -1.05| 0.49   | 1111.9***| 5655|
| Slovakia    | 1.24  | 0.05  | 0.04 | -0.98  | 176.7*** | 4349| Mexico      | 1.18  | 0.03  | 0.12 | -0.57  | 91.97*** | 5642|
| Slovenia    | 1.14  | 0.05  | 0.92 | 0.10   | 467.5*** | 3243| Panama      | 0.90  | 0.28  | -0.57| -1.44  | 794.14** | 5635|
| Spain       | 1.16  | 0.03  | -0.05| -0.60  | 86.81*** | 5655| Argentina   | 1.14  | 0.13  | -2.66| 5.94   | 15,030** | 5655|
| Sweden      | 1.15  | 0.04  | 0.08 | -0.64  | 103.7*** | 5655| Brazil      | 1.15  | 0.03  | 0.14 | -0.51  | 81.03**  | 5655|
| Switzerland | 1.15  | 0.03  | 0.21 | 0.30   | 65.84*** | 5655| Colombia    | 1.17  | 0.03  | -0.04| -0.99  | 154.5*** | 3698|
| UK          | 1.15  | 0.04  | 0.56 | 0.02   | 303.6*** | 5655| Venezuela   | 1.07  | 0.28  | -2.26| 4.16   | 8935.8** | 5655|
| Canada      | 1.17  | 0.04  | -0.29| -0.50  | 143.3*** | 5655| Egypt       | 1.08  | 0.29  | -2.36| 3.89   | 7219.5** | 4610|
| Bermuda     | 1.17  | 0.05  | -0.92| 1.21   | 1123.9*** | 5544| Russia      | 1.21  | 0.03  | 0.01 | -0.06  | 0.96***  | 4684|
| USA         | 1.15  | 0.05  | 0.27 | -0.70  | 188.9*** | 5655| Turkey      | 1.18  | 0.03  | 0.69 | 0.83   | 619.1*** | 5655|
| Chile       | 1.18  | 0.04  | 0.09 | -0.89  | 195.7*** | 5655| Bangladesh  | 1.19  | 0.04  | -0.05| 0.21   | 7.27**   | 2785|
| Australia   | 1.14  | 0.03  | 0.01 | 0.06   | 1.052*** | 5655| Costa Rica  | 1.02  | 0.201 | -2.35| 6.59   | 15,424** | 5628|
| NeZealand   | 1.16  | 0.02  | -0.08| -0.31  | 20.87*** | 3827| Iceland     | 1.16  | 0.04  | 0.39 | 1.16   | 468.8*** | 5655|
| Cyprus      | 1.13  | 0.09  | 1.39 | 1.39   | 1108.8** | 2870|            |       |       |      |        |          |     |

Note: Panel A and Panel B report the descriptive statistics of the approximate entropy for the DMs and EMs. We follow IFC to classify the sample markets into DMs and EMs based on the level of per capita gross national income (PGNI). SD denotes the standard deviation, and JB indicates Jarque–Bera normal test. Skew and Kurt are skewness and kurtosis, respectively. *** and ** denote significance at 1% and 5% level, respectively.
Panel A: Elbow statistics

Panel B: Silhouette statistics

Panel C: Gap statistics

Fig. 10 Cluster specification test. Note: The three statistics specify the robust number of clusters as 2 for the sample
Fig. 11 Evolution of stock market efficiency in developed markets (100 random sequences). Note: Figure presents the degree of time-variation in the efficiency level of developed markets measured by entropy in the 100 random sequences.
Fig. 12 Evolution of stock market efficiency in developed markets (150 random sequences). Note: Figure presents the degree of time-variation in the efficiency level of developed markets measured by entropy in the 150 random sequences.
Fig. 13  Evolution of stock market efficiency in developed markets (300 random sequences). Note: Figure presents the degree of time-variation in the efficiency level of developed markets measured by entropy in the 300 random sequences.
Fig. 14  Evolution of stock market efficiency in emerging markets (100 random sequences). Note: Figure presents the degree of time-variation in the efficiency level of emerging markets measured by entropy in the 100 random sequences.
Fig. 15 Evolution of stock market efficiency in emerging markets (150 random sequences). Note: The figure presents the degree of time-variation in the efficiency level of emerging markets measured by entropy in the 150 random sequences.
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Fig. 16 Evolution of stock market efficiency in emerging markets (300 random sequences). Note: Figure presents the degree of time-variation in the efficiency level of emerging markets measured by entropy in the 300 random sequences.
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