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On the Evolution of the Stock Market Efficiency: Evidence From Emerging Markets

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ABSTRACT

The study of market efficiency is one of the most covered topics in the field of financial markets, with the Efficient Market Hypothesis gathering devotees as well as several critics. The perception of markets as agents with an adaptive nature gave rise to the Adaptive Market Hypothesis (AMH). This paper aims to combine this evolutionary view of market efficiency with the need to assess the behavior of emerging markets over the years. The empirical method selected was the Adjusted Market Inefficiency Magnitude. The sample consists of daily returns between 2005 and 2023 for six stock indices, namely the Indian (BSESN), Brazilian (BVSP), Chinese (CSI300), South African (JALSH), South Korean (KS11), and Taiwanese (TWII), representing the emerging economies bloc. Our findings show greater proximity to the efficiency framework proposed by the AMH, with the emerging markets evidencing an evolutionary behavior, combining a state of generalized efficiency with periods of remarkable inefficiency. Also, the observable synchronization between evolutionary moments and the occurrence of major economic events, both systemic and related to a particular economy, reinforces the need to frame the study of the efficiency of this category of markets within the global economic framework.

JEL Classification: G10, G14

1 | Introduction

The term "emerging markets" is used to refer to economies that are experiencing a period of accelerated economic growth and are in the process of convergence with the so-called developed markets (Van Agtmael 2007). Despite the usual association, the income growth factor is not the only characteristic that defines an emerging market. In addition to outperforming its peers in this field, this range of economies also stands out for its growing participation in global trade as well as its integration into financial markets.

Since its inclusion in economic terminology, the prominence of this new bloc of economies has been on an upward curve, and according to the latest data released by the IMF Outlook in April 2024, their population corresponds to approximately 86% of the world's population.[1] In terms of economic size, emerging markets accounted in 2022 for around three-fifths of total global GDP measured in purchasing power parity terms, 41% of total world exports, and approximately 35% of total imports.[2] Additionally, in terms of financial development, Goldman Sachs' projections indicate that the weight of market capitalizations of the equity markets representing these economies will correspond to 37% of the total global equity market by the end of this decade, reaching 47% by 2050.[3] These figures are more illustrative than ever, given the strong connections established in an increasingly global world in terms of economic, finance, trade, and geopolitical dynamics.

Combining the evolution observed in the literature regarding the analysis of market efficiency mechanisms with the relevant role played by emerging markets in the dynamics of the financial system on a global scale, this paper aims to assess the evolutionary process of stock market efficiency. A particular focus will be given to emerging markets, seeking to shed some light on a maturation process that this category of markets may have been going through over the years. In coordination with this central line of research, there is also an interest in fitting this process of evolution into the global economic picture. In this sense, the results obtained will be discussed in the light of the economic environment that surrounds them, paving the way for the development of more in-depth studies on the impact of certain important economic moments on the levels of efficiency observed in emerging markets.

In terms of academic relevance, the present paper seeks to identify itself as an addition to the new line of literature that has been drawn up within the study of market efficiency. Aware of the fundamental basis given by the Efficient Market Hypothesis (EMH) theory and the healthy discussion about its applicability over time in different markets, the present work will approach the concept of efficiency in the form of a spectrum, evolving within different contexts and time intervals. The main goal is to close the gap in the existing literature, which essentially focuses on approaching the topic from a black and white perspective, seeking to answer the question “Are markets efficient?” This research aims to take this question off the table and replace it with the following: “How efficient are markets and how does their level of efficiency evolve?”

Based on the *Adjusted Market Inefficiency Magnitude* (AMIM) measure, established in the empirical literature on the study of market efficiency by Tran and Leirvik (2019) and still not formally applied in the study of efficiency in emerging markets, the empirical approach adopted for this study will focus on a sample made up of six stock market indexes, namely the Indian (BSESN), Brazilian (BVSP), Chinese (CSI300), South African (JALSH), South Korean (KS11), and Taiwanese (TWII), representative of the emerging economies bloc. The time horizon covered is 2005–2023, and the frequency of observations (historical returns) is daily. In our opinion, this method is particularly suitable for studying emerging markets since, hypothetically, those markets are more sensitive to shocks that can alter market efficiency, yielding periods of higher or lower efficiency.

The remaining content of the paper is organized as follows: Section 2 reviews the existing literature on the concept of market informational efficiency, also portraying it in the context of emerging markets. Section 3 describes the method applied and the inputs used in its computation. Section 4 presents the empirical results obtained and discusses them in the light of the central research objectives and the established literature. Section 5 reinforces the main conclusions of the paper, the contributions of the results obtained and their limitations as well as possible avenues for future research.

2 | Literature Review

2.1 | EMH: Background and the Emergence of the AMH

Market efficiency constitutes a core concept in financial economics and is traditionally formalized through the EMH. According to Fama (1965), a market is informationally efficient when asset prices fully reflect all available information. This definition provided the theoretical foundation for a vast empirical literature and established market efficiency as a benchmark rather than a directly observable condition. Fama (1970) further identified the key assumptions underpinning informational efficiency, namely, the absence of transaction costs, the free and universal availability of information, and homogeneous expectations among investors, and distinguished between weak, semi-strong, and strong forms of efficiency.

Early empirical studies largely supported the weak-form EMH, with asset returns exhibiting behavior consistent with a random walk (Fisher and Lorie 1964; Malkiel 1973). Under weak-form efficiency, historical price and volume information is fully incorporated into current prices, rendering technical trading strategies unable to generate persistent abnormal returns. However, from the 1980s onwards, a growing body of empirical evidence challenged the EMH, documenting systematic patterns in returns that appeared inconsistent with market efficiency. These include overreaction and underreaction effects (De Bondt and Thaler 1985; Chopra et al. 1992), momentum strategies (Jegadeesh and Titman 1993; Rouwenhorst 1998), post-earnings announcement drift (Bernard and Thomas 1989), and the profitability of insider trading (Seyhun 1986).

While much of this evidence undermined the semi-strong and strong forms of efficiency, debate increasingly centered on the validity of the weak form. As noted by Malkiel (2003), empirical conclusions regarding efficiency are highly sensitive to market conditions, sample properties, and methodological choices, contributing to the proliferation of studies focused on market anomalies. These limitations highlighted the difficulty of reconciling empirical findings with the static assumptions of the EMH and motivated the search for alternative frameworks capable of accommodating time variation in market behavior.

The emergence of behavioral finance further challenged the EMH by questioning the assumption of fully rational investors. This literature emphasized the role of psychological biases, heuristics, and limits to arbitrage in shaping asset prices (Selten 1990; Barberis and Thaler 2003; Ritter 2003). Within this broader intellectual, Lo (2004, 2005) proposed the Adaptive Market Hypothesis (AMH), which conceptualizes financial markets as evolving systems in which efficiency depends on the interaction between market participants, institutional structures, and changing economic environments. Under the AMH, markets are neither permanently efficient nor inefficient; instead, efficiency emerges and dissipates as investors adapt through learning and competition.

Following the implementation of this adaptive perspective, a substantial empirical literature has tested the AMH across different markets, asset classes, and data frequencies (Lim 2007; Ito and Sugiyama 2009; Kim et al. 2011; Urquhart and Hudson 2013; Urquhart and McGroarty 2014, 2016). Despite methodological diversity, these studies consistently conclude that market efficiency exhibits time-varying behavior, lending support to the adaptive view.

Recent research has continued to explore the dynamic nature of market efficiency, particularly through the lens of the AMH. Meng (2021), using high-frequency order book data and an S&P 500 exchange-traded fund (SPY), showed that informational efficiency fluctuates over time and that high-frequency traders strategically adjust their behavior in response: they actively process information during low-efficiency periods and shift to passive market-making when efficiency increases, lending support to AMH. Similarly, Karasiński (2025) finds that the weak-form efficiency of major cryptocurrencies varies across time and frequencies, with higher-frequency data revealing greater predictability. Although most cryptocurrencies remain largely unpredictable, efficiency tends to decline at finer time scales, suggesting exploitable short-term anomalies and raising regulatory concerns. In contrast, Hřebačka (2025) argues that many empirical patterns attributed to AMH in U.S. equities can instead be explained by business cycle fluctuations and risk aversion, concluding that the EMH remains the more robust framework. Together, these studies highlight ongoing debate between AMH and EMH perspectives, with evidence of time-varying efficiency in some markets but competing interpretations regarding its origins and implications.

Overall, the transition from a binary assessment of whether markets are efficient towards an analysis of how efficiency evolves over time represents a significant conceptual shift. This dynamic perspective provides a more flexible framework for empirical investigation, particularly in market environments characterized by structural change and institutional frictions.

2.2 | Efficiency in the Context of Emerging Markets

Emerging equity markets constitute a particularly suitable environment for testing market efficiency, given the prevalence of structural frictions that challenge the assumptions underlying the EMH. These markets are typically characterized by lower liquidity, thin trading, higher volatility, informational asymmetries, and evolving institutional and regulatory frameworks (Antoniou et al. 1997). Consequently, a substantial strand of the literature argues that emerging markets tend to exhibit lower levels of informational efficiency than developed markets, especially in weak-form terms (Bekaert and Harvey 2003).

Market efficiency in emerging economies, however, is not static. As markets mature and integrate into the global financial system, efficiency is expected to evolve alongside improvements in market microstructure, regulatory quality, and information dissemination. Empirical studies associate higher efficiency levels with factors such as market size, reduced transaction costs, technological development, and enhanced institutional frameworks (Risso 2009; Lagoarde-Segot and Lucey 2008; Cajueiro and Tabak 2004; Sharma and Thaker 2015). Nonetheless, the role of financial liberalization remains ambiguous, with evidence suggesting that liberalization alone may not suffice to ensure efficiency once broader institutional constraints are considered (Kawakatsu and Morey 1999).

Empirical findings on weak-form efficiency in emerging markets are mixed. On one side, several studies report evidence consistent with the random walk hypothesis in specific markets or sub-periods. For instance, Ojah and Karemera (1999) find support for weak-form efficiency in major Latin American markets, while Narayan and Smyth (2004) and Al-Khazali et al. (2007) obtain similar results for selected Asian and MENA markets after controlling for structural breaks and thin trading effects. On the other side, a considerable body of literature documents systematic deviations from random walk behavior. Claessens et al. (1995) provide early evidence that a broad set of emerging markets exhibits return predictability and anomalies comparable to those observed in developed markets, suggesting the presence of exploitable inefficiencies. Subsequent studies confirm these findings across regions and methodologies, identifying calendar effects, variance-ratio rejections, and other forms of predictable return behavior (Urrutia 1995; Poshakwale 1996; Chaudhuri and Wu 2003; Hoque et al. 2007; Hamid et al. 2017).

More recent contributions emphasize that such conflicting evidence may reflect the time-varying nature of market efficiency rather than fundamental inconsistencies in empirical testing. In this context, Smith (2012) provides evidence from a sample of European emerging markets showing substantial variation in return predictability over time, with efficiency levels responding to major economic and financial events. This dynamic interpretation is further reinforced by studies employing rolling-window techniques, time-varying parameters, and alternative efficiency measures, which consistently document alternating periods of efficiency and inefficiency (Jefferis and Smith 2005; Chong et al. 2012; Niemczak and Smith 2013; Hull and McGroarty 2014).

These findings align closely with the AMH. Hiremath and Kumari (2014) argue that the AMH is particularly well suited to emerging markets, as it explicitly accommodates market frictions, institutional constraints, and the evolutionary nature of investor behavior. Empirical evidence from a wide range of emerging economies supports this perspective, showing that profitability of trading strategies and return predictability fluctuate across time and market conditions rather than disappearing permanently (Hiremath and Narayan 2016; Xiong et al. 2019; Lekhal and El Oubani 2020; Munir et al. 2022; Cruz-Hernández and Mora-Valencia 2024; Said et al. 2024).

Overall, the empirical literature suggests that while emerging markets frequently reject the weak-form EMH, these rejections are neither uniform nor persistent. Instead, market efficiency appears to be context-dependent and time-varying, shaped by institutional development, market frictions, and changing economic conditions. This evidence provides strong support for adopting adaptive frameworks when analyzing efficiency in emerging markets and underpins the empirical approach followed in the present study.

3 | Methodology and Data

In this section, we begin by contextualizing the empirical method applied in this study in the light of the established empirical literature as well as the central research objectives. Next, the efficiency measure, AMIM, is introduced, and its computation is described. Finally, the sample used is presented along with its transformative process in light of the empirical method stated.

Lim and Brooks (2011), in their survey, reiterate the presence of a focus in the empirical literature on the study of weak-form efficiency. Within this category of studies, it is also possible to identify a subset dedicated to testing the predictability of security returns based on the past behavior of their prices, as well as another focused on examining the profitability of trading strategies based on past returns (Park and Irwin 2007; Chou et al. 2007). The empirical method applied in this paper falls into the first category of studies, and it is therefore wise to recommend caution when analyzing the results produced from a practical point of view, since the profits made from a hypothetical degree of inefficiency identified depend on the effectiveness of the trading strategy applied, an aspect which is beyond the scope of this article.

The bulk of empirical studies into the weak form of efficiency attempt to answer the question “Is the market under study weak form efficient in absolute terms?” The focus on this question assumes that the level of efficiency remains constant throughout the estimation period. A series of statistical tests is applied to detect deviations from a random walk in returns time series, such as linear serial correlations, unit root, non-linear dependence, and long memory (Mandelbrot 1971; Lo and MacKinlay 1988; Lean and Smyth 2007; Scheinkman and LeBaron 1989).

The incompatibility between the EMH framework and the growing school of behavioral finance on fundamental topics such as the behavioral profile of investors and its impact on decision-making and consequent market response (see the debate in Malkiel et al. 2005) has led to a certain degree of skepticism about the viability of traditional empirical methods of measuring efficiency. It is in the sphere of the convergence between the two ideals of efficiency that a new range of empirical studies has emerged, seeking to approach market efficiency open to the possibility of it varying over the period under analysis, in line with the theoretical framework established by the AMH in Lo (2004). Among these methods, three stand out, namely the analysis of non-overlapping sub-periods, time-varying parameter models, and moving estimation window models.

The analysis of non-overlapping sub-periods brings together a collection of studies that advocate greater importance in understanding the factors that guide markets towards periods of efficiency/inefficiency (Antoniou et al. 1997; Basu et al. 2000; Jain 2005; Hoque et al. 2007). The discrete evaluation of efficiency carried out by this segment of empirical methods has been criticized and, as a result, an emerging literature has aimed to capture the time-varying weak-form stock market efficiency, proposing to evaluate market efficiency as a continuous process (Zalewska-Mitura and Hall 1999). The additional insights produced by time-varying parameter models come from the use of another group of studies based on rolling estimation windows. Their application essentially captures the persistence of the deviations observed in stock prices in relation to a random walk benchmark over the period of analysis, making it possible to compare the concept of efficiency between different assets as well as to identify events that coincide with periods of inefficiency. This approach opens the door to the possibility of identifying and exploring the potential determinants of the weak form of efficiency in different markets (Alvarez-Ramirez et al. 2008; Lim and Brooks 2009).

The method applied in this paper combines the nature of the last two groups presented, resulting in a robust means of capturing the evolution of the efficiency of the different markets under study, as well as an analysis of the efficiency observed in them both in relative terms and in the context of different economic periods.

3.1 | The AMIM

The study of the evolution of the efficiency levels of emerging markets will be carried out in this paper through the application of the measure entitled AMIM, introduced in the literature by Tran and Leirvik (2019).

The AMIM is calculated using the autocorrelation coefficients of a stock return time series and the associated confidence intervals for those coefficients. The first step is to compute the Market Inefficiency Magnitude (MIM), based on the measure applied by Noda (2016) entitled time-varying degree of market efficiency, and then use the confidence intervals to make the adjustment that allows us to obtain the AMIM. This step results in a robust measure against insignificant correlation.

The output resulting from the application of the method has a maximum ceiling of 1. The interpretation of the output generated is simple: the AMIM increases as the level of efficiency of the asset under study decreases. For analysis purposes, the production of a negative output indicates an efficient market, while a positive output implies the existence of an inefficient market.

The Adjusted Market Efficiency Magnitude used in our study provides a continuous and direct measure of efficiency that is robust across different data frequencies, making it particularly suitable for analyzing stock markets with low liquidity – such as those typically found in emerging economies (Tran and Leirvik 2019, 2020).

The nature of the method, as well as its simplistic output, allows for a relative approach to the concept of efficiency. This research will seek to make use of this feature to evaluate the concept of efficiency over the period of analysis and to make a comparison between the different markets studied.

3.2 | Model Setup

This subsection presents the methodology following the paper from Tran and Leirvik (2019) closely. Interested readers should look for more details about the method in that paper.

3.2.1 | Auto-Correlation Coefficients Computation

According to the framework established in Fama (1970), in a weak-form efficient market, when we apply an autoregressive process AR(q) to the return series (r_t) in its own lags, it is not possible to explain the dynamics of returns over time. When aligned with the EMH, the AR(q) model:

$$r_t = \propto + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \dots + \beta_q r_{t-q} + \varepsilon_t. \tag{1}$$

If the EMH holds, the model should yield coefficients that are either close to zero or not significantly different from zero. However, if the EMH is violated, the coefficients will be significantly different from zero. A range of studies, including Lo (2004), apply the first-order autoregressive model to assess the level of efficiency. Aware that the presence of a greater number of lags with significant coefficients implies more robust evidence against an efficient market, the model applied does not select any number of lags to be computed from the very beginning.

From Equation (1), the column vector $\hat{\beta}$, which contains the estimated coefficients, follows an asymptotic distribution:

$$\hat{\beta} \sim \mathrm{N}\,(\beta, \Sigma). \tag{2}$$

Here, β denotes the true vector of autocorrelation coefficients, and Σ represents the asymptotic covariance matrix of the estimated $\hat{\beta}$ vector. This matrix can be decomposed into two triangular matrices using the Cholesky decomposition: $\Sigma = LL'$.

Because the estimated coefficients may have varying standard errors and could exhibit correlation, it is necessary to standardize the $\hat{\beta}$ vector. This is done by multiplying it by the inverse of the triangular matrix L, leading to:

$$\hat{\beta}^{standard} = L^{-1}\hat{\beta}. \tag{3}$$

Now, under the null hypothesis of market efficiency ($\beta = 0$), $\hat{\beta}^{standard}$ should be normally distributed as follows:

$$\hat{\beta}^{standard} \sim \mathrm{N}\,(0,\ I). \tag{4}$$

With I corresponding to the identity matrix. The normalization process carried out makes each of the elements present in $\hat{\beta}^{standard}$ independent, and the standardized coefficients will be proved useful later in the construction of the efficiency model based on $\hat{\beta}^{standard}$.

3.2.2 | MIM

The next step involves constructing a raw measure of market inefficiency, referred to as the MIM:

$$MIM_t = \frac{\sum_{j=1}^{q} \left|\hat{\beta}_{j,t}^{standard}\right|}{1 + \sum_{j=1}^{q} \left|\hat{\beta}_{j,t}^{standard}\right|}. \tag{5}$$

In this formula, MIM_t represents the MIM at time t, and $\hat{\beta}_{j,t}^{standard}$ denotes the j^{th} autocorrelation coefficient from Equation (1) after being standardized.

Given the central focus on capturing auto-regressive coefficients other than zero in order to assess moments of violation of the assumption of weak-form efficiency, the MIM is constructed based on absolute values, thus eliminating the sign effect. In practice, the absolute values of $\hat{\beta}_{j,t}^{standard}$ are used when summing the coefficients, which prevents the offsetting effect of positive and negative values. The use of standardized $\hat{\beta}$ coefficients is also advantageous from an empirical standpoint: once standardized, these autocorrelation coefficients can be employed to derive a unified set of confidence intervals for MIM under the null hypothesis of market efficiency. This approach simplifies the process by reducing the overall computational complexity. This measure of efficiency varies continuously from 0 (representing a very efficient market) to almost 1 (an inefficient market). From an interpretative point of view, when comparing two different assets, the one with a higher MIM will be more influenced by its past behavior than the one with a lower MIM.

The non-overlapping window approach is used to calculate the MIM over the period under analysis, allowing us to obtain the raw efficiency degree for each time interval (trading year). In the discussion of the empirical results, the rolling window method is also applied, constituting a robustness check on the outputs obtained. Alongside this double check stage, the mathematical nature of the method, which results in a continuous output, allows us to avoid individual revisions in the search for economic rationale behind the results obtained, a problem present in some literature (Ito et al. 2014; Noda 2016), generating greater interpretative soundness.

3.2.3 | Confidence Intervals Estimation

At this point, although the issue of the discontinuity of the output generated by the MIM measure has been accommodated, it is important to note that this raw measure of efficiency can offer a false sense of efficiency/inefficiency. As previously discussed, once the sign effect is removed, the MIM will exhibit a positive correlation with the number of lags identified during the initial stage of the model's construction. The challenge naturally arises in accommodating the presence of insignificant lags that may overestimate the final measure, distorting our interpretation of the results obtained. The solution is to correct the MIM by computing its confidence intervals. The latter will be obtained through simulations, since the normal distribution followed by the elements present in the $\hat{\beta}^{standard}$ vector obtained in Equation (4) allows us to identify the confidence intervals of MIM under the null hypothesis of market efficiency using this method.

First, we will simulate 100,000 observations for each element in $\hat{\beta}^{standard}$, following a normal distribution. This simulation will generate 100,000 observations of the MIM measure under the null hypothesis of market efficiency for each identified lag count. Given that MIM ranges from 0 to 1, the confidence interval for MIM under the null hypothesis is defined by the interval from 0 to the 95th percentile obtained. The final output of this process will be a single confidence interval value for each number of lags.

3.2.4 | AMIM

The last step in computing the empirical model is to obtain the AMIM, which comes from the adjustment made to the MIM by applying the confidence intervals estimated previously:

$$AMIM_t = \frac{MIM_t - R_{CI}}{1 - R_{CI}}. \tag{6}$$

Equation (6) is divided into two components. The numerator represents the adjustment applied to the MIM measure, subtracting the range between the MIM and the 95% confidence interval under the null hypothesis of market efficiency. The denominator, where the R_{CI} is subtracted from the unit, serves the purpose of creating a uniform basis for comparison across different assets, which will inevitably be associated with different values for MIM and R_{CI} in different time periods. The measure obtained is now suitable for a relative assessment of the concept of efficiency.

With both parameters of Equation (6) between 0 and 1, the AMIM measure will find a maximum ceiling of 1, with the possibility of assuming negative values. As a result of this construction, when $AMIM_t < 0$, the null hypothesis of market efficiency cannot be rejected. On the other hand, a positive $AMIM_t$ value indicates the presence of a significantly inefficient market. This degree of inefficiency increases as $AMIM_t$ increases.

3.3 | Data

In order to align the empirical method with the focus of this research, six indices representative of the emerging economies bloc were selected (using the market capitalization of these markets in 2023 as the selection criterion), namely BSESN (India), BVSP (Brazil), CSI300 (China), JALSH (South Africa), KS11 (South Korea), and TWII (Taiwan). The data on the daily prices of the different indices was collected from Eikon Datastream. Logarithmic returns were computed based on these daily prices, resulting in a daily frequency of returns covering a 19-year period from 2005/01/03 to 2023/12/29. The start of the period was chosen in order to have a longer and complete sample for all the indexes. Table 1 shows the descriptive statistics of the logarithmic daily returns of the indices studied over this period. The Indian index (BSESN) had the highest average daily return, while the Brazilian index (BVSP) was the most volatile over the time horizon analyzed. The highest daily return was recorded by the BSESN, with an appreciation of 6.94%, while its Brazilian counterpart recorded the greatest daily devaluation, amounting to −6.95%.

This sample will be used to compute the AMIM. More specifically, the aim is to approach this model in two different ways. In the first phase, the model will be calibrated to compute an AMIM and MIM value for each year of the estimation period, resulting in a more segmented analysis. AMIM will also be estimated on a daily basis using 1-year rolling-window data, in line with the procedure observed in Tran and Leirvik (2019). The aim of this approach is to identify the evolutionary behavior of this measure over the period under analysis.

4 | Empirical Results and Discussion

This section presents and discusses the results obtained by applying the empirical method described above. The values obtained for the MIM and AMIM metrics are analyzed in the context of the reported literature. It is also of interest to use these metrics to characterize the evolution of the efficiency observed in emerging markets, as well as to shed some light on the impact that major economic events may have on the efficiency levels of this category of economies.

First, we return the outputs concerning the evolution of the MIM metric, applying the non-overlapping window, over the defined study period. Although incorporating the autocorrelation dynamics of the returns in these final figures and describing a clear fluctuation, the values reported by the MIM are not robust enough to characterize the evolution of the efficiency levels of the indices that make up our sample, both from a historical and relative perspective.

To illustrate this lack of robustness, Figure 1 shows the annual MIM values reported for two stock indices, the Brazilian (BVSP) and the Chinese (CSI 300). Although they describe different behaviors, the truth is that it is not possible to establish a relative assessment of the efficiency levels of these two markets. As an example, at first glance, we could be led to believe that the outbreak of the Global Financial Crisis (GFC) (2007–2008) was associated with a higher level of relative inefficiency in the Brazilian financial market ($MIM_{2007} = 0.56$ and $MIM_{2008} = 0.79$), compared to its Chinese counterpart ($MIM_{2007} = 0.15$ and $MIM_{2008} = 0.12$). However, these raw values do not have a common basis for comparison, as the two assets have different confidence intervals for the MIM values obtained at any given time. As a result, a relatively low value of MIM could be associated with a significant level of efficiency or vice versa. The results presented below for AMIM are free of this interpretative obstacle since they originate from the adjustment of MIM to its confidence intervals.

Table 2 gives a brief overview of the values obtained for the AMIM by applying a non-overlapping window method. For all the markets illustrated in the sample under analysis, the results obtained report varying levels of efficiency over time, in line with the literature that expresses this evolutionary nature of market efficiency (Lo 2004, 2005). Another insight we can derive from Table 2 is the presence of efficiency as a general rule throughout the period under analysis in all the indices analyzed, with particular emphasis on the Chinese (CSI300) and South Korean (KS11) indices. The negative average AMIM values observed in the six indices, together with the presence of negative values in this metric in 75% of the 19 years observed (except for the Indian index, which has a $Q0.75 = 0.14$), allow us to conclude that these representative markets of the

TABLE 1 | Summary statistic of indexes logarithmic daily returns over the period 2005–2023.

Index	*n*	Mean	SD	Median	Min	Max	Skew	Kurtosis
BSESN	4710	0.00022	0.00589	0.00039	−0.06124	0.06944	−0.25196	11.99133
BVSP	4701	0.00015	0.00741	0.00030	−0.06946	0.05940	−0.41194	9.03006
CSI300	4619	0.00012	0.00708	0.00027	−0.04210	0.03879	−0.50140	4.21709
JALSH	4748	0.00017	0.00530	0.00031	−0.04441	0.03930	−0.27659	5.59850
KS11	4696	0.00010	0.00530	0.00028	−0.04852	0.04901	−0.47081	8.73189
TWII	4681	0.00010	0.00489	0.00032	−0.02925	0.02834	−0.46063	4.28958

Note: BSESN (India), BVSP (Brazil), CSI300 (China), JALSH (South Africa), KS11 (South Korea), and TWII (Taiwan). Main descriptive statistics of the logarithmic daily returns observed for the indexes under study. The distinction between the number of observations is related to the trading calendar of each market.

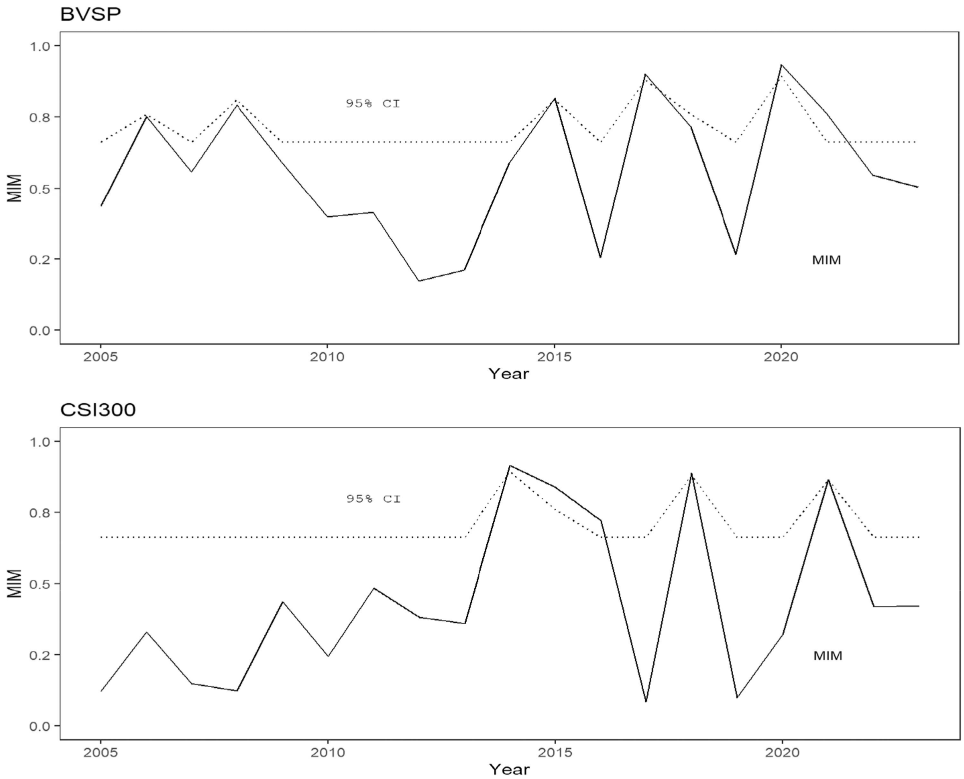

FIGURE 1 | MIM of BVSP and CSI300 indexes. BVSP (Brazil) and CSI300 (China). The MIM measure is estimated here by applying a non-overlapping window method. The solid line represents the MIM values obtained, while the dashed line represents the 95% confidence interval of the MIM under the null hypothesis of market efficiency.

TABLE 2 | Summary statistic of AMIM measure using a non-overlapping window method.

Index	*n*	Mean	SD	Median	Min	Max	Skew	Kurtosis	Q0.25	Q0.5	Q0.75
BSESN	19	−0.35	0.57	−0.46	−1.64	0.36	−0.50	−0.80	−0.73	−0.46	0.14
BVSP	19	−0.44	0.55	−0.31	−1.45	0.39	−0.39	−1.12	−0.76	−0.31	−0.06
CSI300	19	−0.79	0.68	−0.83	−1.71	0.32	0.21	−1.35	−1.38	−0.83	−0.26
JALSH	19	−0.63	0.65	−0.69	−1.80	0.44	−0.01	−1.15	−1.05	−0.69	−0.08
KS11	19	−0.75	0.72	−0.54	−1.90	0.19	−0.20	−1.60	−1.43	−0.54	−0.11
TWII	19	−0.63	0.63	−0.70	−1.66	0.21	−0.17	−1.57	−1.12	−0.70	−0.03

Note: BSESN (India), BVSP (Brazil), CSI300 (China), JALSH (South Africa), KS11 (South Korea), and TWII (Taiwan). The AMIM measure is estimated on an annual basis by applying independent and fixed-size windows (length equivalent to one trading year).

emerging economies bloc can be overall characterized as efficient markets. This evidence is in line with Galindo et al.'s (2007) position, which argues that as they face a process of development and financial integration, this category of markets tends to observe greater levels of efficiency. From this point of view, our results point to the possible presence of the phenomenon of the maturation of these markets.

The use of a 1-year (252-day) rolling window, although standard in studies following Tran and Leirvik (2019), may obscure abrupt structural breaks in efficiency if such changes occur within the boundaries of the estimation window. Shorter windows tend to detect turning points more rapidly, while longer windows produce smoother efficiency paths at the cost of responsiveness.

As a robustness check to the results obtained above, the values estimated for the AMIM using a rolling window provide the same qualitative insights (see Table 3). In fact, applying a 100-day Moving Average to the results obtained allowed us to create a more accurate picture of the evolutionary trends in market efficiency. This indicator reinforces the alternation experienced in the markets between a state of efficiency and inefficiency, as well as the dynamic response of the different markets during and after periods of turbulence triggered by crises, speculative bubbles, and so forth.

Based on the AMIM results produced by both procedures, it is possible to derive the existence of informational efficiency as the general rule in all the indices analyzed (see the mean values of AMIM in both Tables 2 and 3), which coexists with the presence of periods of inefficiency (see Figure 2), in line with the framework of the AMH set out by Lo (2004). This evidence is also consistent with the thesis that investors' decision-making has an impact on the behavior of the

TABLE 3 | Summary statistic of AMIM measure using a rolling window method.

Index	*n*	Mean	SD	Median	Min	Max	Skew	Kurtosis	Q0.25	Q0.5	Q0.75
BSESN	4462	−0.03	0.15	−0.02	−0.42	0.48	0.38	−0.58	−0.18	−0.02	0.07
BVSP	4374	−0.09	0.15	−0.15	−0.42	0.59	1.23	1.12	−0.21	−0.15	−0.02
CSI300	4200	−0.09	0.14	−0.11	−0.42	0.40	0.11	1.68	−0.14	−0.11	−0.02
JALSH	4317	−0.09	0.17	−0.13	−0.38	0.55	1.35	1.82	−0.21	−0.13	−0.03
KS11	4441	−0.06	0.13	−0.05	−0.36	0.51	0.31	−0.16	−0.18	−0.05	−0.01
TWII	4238	−0.03	0.13	−0.04	−0.25	0.46	0.28	−0.54	−0.11	−0.04	0.07

Note: BSESN (India), BVSP (Brazil), CSI300 (China), JALSH (South Africa), KS11 (South Korea), and TWII (Taiwan). The AMIM measure is estimated daily, assuming a rolling window extension equal to one trading year (252 trading days).

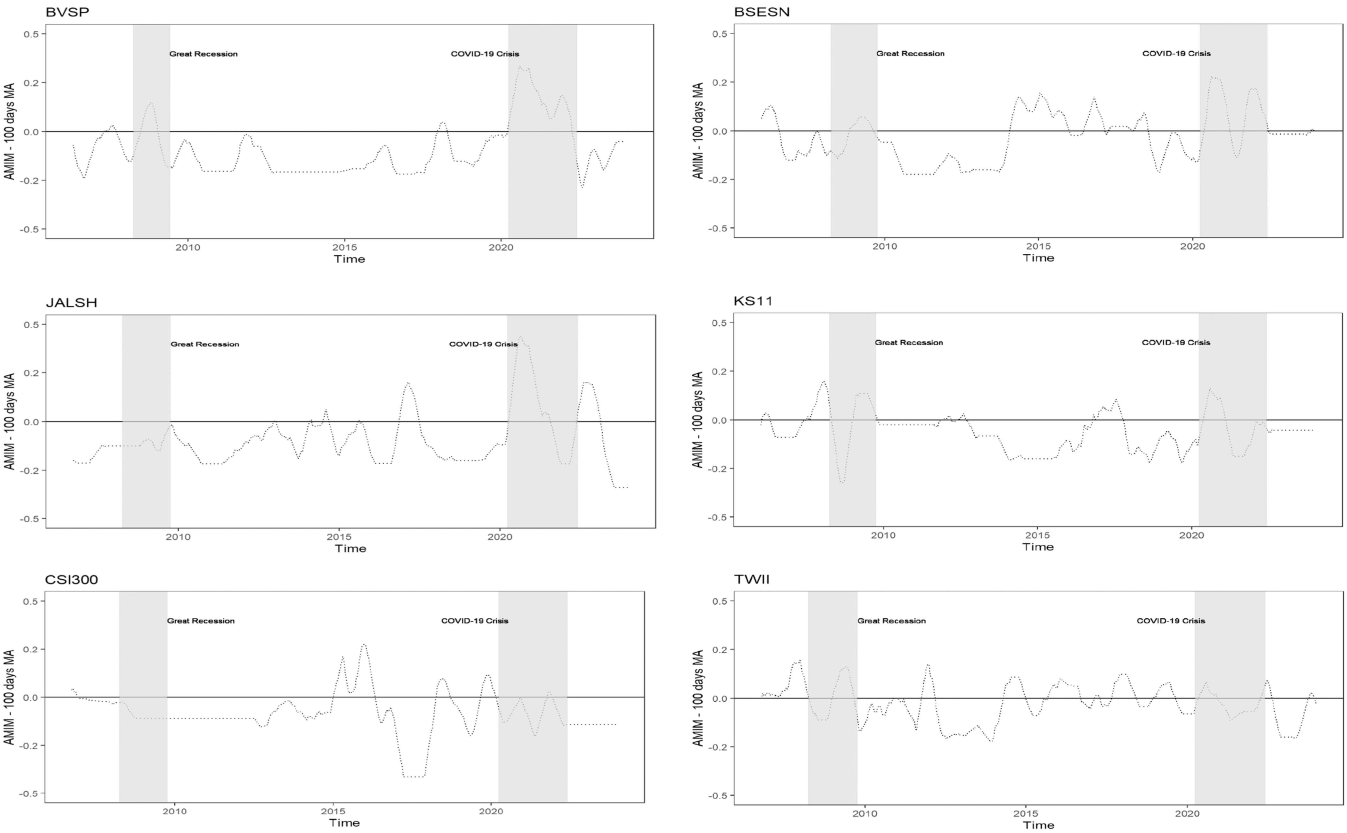

FIGURE 2 | Behavior of the AMIM measure in systemic economic events. BSESN (India), BVSP (Brazil), CSI300 (China), JALSH (South Africa), KS11 (South Korea), and TWII (Taiwan). The dotted line represents the 100-day moving average of the AMIM values. Shaded areas comprise, respectively, the Global Financial Crisis, initiated in September 2008, and the Pandemic Crisis, beginning in February 2020.

markets, which have a dynamic nature based on a continuous process of learning and adapting on the part of the economic agents that make them up. Overall, the results show a closer relation with the dynamic behavior of the concept of efficiency accommodated by the AMH, in comparison to the inflexible positioning of the EMH, in agreement with Hiremath and Kumari (2014).

Concerning the relative analysis of market efficiency across the stock indices included in our sample, the evolution of the 100-day moving average of the AMIM values reveals a distinctly heterogeneous pattern of behavior across markets (see Figure 2). Although all indices were exposed to major systemic shocks that affected global financial markets over the period under analysis, the trajectories of informational efficiency differ markedly across countries. This heterogeneity, observed both during periods of financial turmoil and in their aftermath, suggests that, beyond global factors, market-specific characteristics and internal structural features play a significant role in shaping the evolution of market efficiency.

Focusing on the two most salient systemic episodes over the sample period – the GFC, initiated in September 2008, and the Pandemic Crisis, beginning in February 2020 – it is possible to identify distinct responses in terms of informational efficiency across the emerging stock markets analyzed. The GFC appears to have had particularly pronounced adverse effects on the informational efficiency of the Brazilian (BVSP), Indian (BSESN), South Korean (KS11), and Taiwanese (TWII) stock markets, with extended periods of elevated inefficiency following the onset of the crisis. This deterioration in efficiency is consistent with the severe disruption to global capital flows, heightened uncertainty, and stress in financial intermediation mechanisms that characterized this episode.

The Pandemic Crisis, by contrast, generated a different but equally significant pattern of disruption. In this case, the negative impact on informational efficiency is especially evident in the Brazilian (BVSP), South African (JALSH), Indian (BSESN), and South Korean (KS11) markets. The unprecedented nature of the COVID-19 shock, combined with abrupt policy interventions, supply-chain disruptions, and heightened behavioral responses by investors, appears to have amplified informational frictions and delayed price adjustment processes in these markets. Notably, the Chinese market exhibits a comparatively resilient efficiency profile during most of both crisis periods, suggesting differences in market structure, policy responses, or information dissemination mechanisms.

When the entire sample period is considered, the longest and most pronounced episodes of inefficiency are observed primarily in the Brazilian, South African, South Korean, and Indian stock markets. These prolonged deviations from efficiency appear closely linked to the two systemic crises analyzed, and in particular to the COVID-19 pandemic, which stands out as the episode associated with the most persistent and severe deterioration in informational efficiency across multiple markets. This finding reinforces the view that extreme and multifaceted shocks can generate lasting disruptions to the price formation process, especially in emerging markets where institutional and informational constraints are more pronounced.

Overall, the relative analysis of the indices considered highlights that emerging markets do not respond uniformly to global systemic events. Differences in market integration, regulatory frameworks, investor composition, and microstructural characteristics contribute to the observed diversity in efficiency dynamics. While these markets share certain common features, treating them as a homogeneous group may obscure important cross-country differences in how efficiency evolves over time. Consequently, future research would benefit from a more granular approach that examines the internal mechanisms and country-specific events shaping market efficiency, constructing individual efficiency timelines that better reflect the interaction between global shocks and domestic financial and economic conditions.

As an illustration, Figure 3 identifies, for three of the six indices studied (India, Brazil, and China), specific economic events in each of the markets coinciding with relevant moments in the evolution of the degree of market efficiency. The period 2015–2016 was characterized in the Indian economy by the demonetization process carried out by the government, resulting in a lower flow of liquidity to the stock markets, which, combined with the uncertainty caused by this unexpected policy, resulted in a particularly turbulent period for the country's main stock indices, namely the BSESN (Sutar et al. 2022). Arguably, political instability in Brazil creates uncertainty, deterring investment and distorting market signals, undermining market efficiency. In contrast, China's political and economic stability, along with the strong regulatory role of the People's Bank of China, helps manage risks and maintain investor confidence. This centralized control enables quicker policy responses and greater predictability, contributing to more stable and efficient markets. While not entirely free-market driven, China's structure supports smoother information flow and reduced volatility compared to Brazil. The period of exuberance experienced by the Brazilian stock exchange in the second half of the last decade is also identified, followed by the collapse caused by the pandemic crisis and the turmoil experienced by the global oil markets (Laurini and Chaim 2020). Finally, the AMIM measure also proved capable of identifying the stock market bubble in the Chinese stock market that would burst at the beginning of 2015, causing instability in the global markets with the possibility of a sharp slowdown in an economy that was already particularly important on the international scene. In relation to global events, the period of analysis encompasses two phenomena that are, although in different degrees as mentioned earlier in this report, captured by the efficiency measure applied, namely the GFC of 2008, as well as the crisis caused by the COVID-19 pandemic. It is important to emphasize that an in-depth study of these events and their impact on the market efficiency of the indices analyzed here should be the focus of future research of a more causal nature, with this method serving as a support tool to help identify noteworthy evolutionary moments.

Nevertheless, the seemingly superior efficiency of the Chinese market, as reflected in the CSI 300 persistently low AMIM values, must be interpreted with caution. The institutional structure of China's financial system, characterized by active regulatory intervention, price-limit mechanisms, trading halts, and state-directed market support, can mechanically suppress return volatility and reduce short-term autocorrelation. Such interventions may therefore generate what can be termed "pseudo-efficiency": a statistical appearance of weak-form efficiency that does not necessarily reflect a high level of informational efficiency. By dampening noise trading and constraining market reactions to new information, these measures can reduce the magnitude of inefficiencies captured by AMIM without necessarily improving the underlying information environment. On the other hand, evaluating whether China's high efficiency scores reflect genuine market maturity or intervention-driven dampening requires a broader perspective on its temporal behavior. The stability of AMIM during global episodes such as the GFC or the COVID-19 shock may suggest a more developed market structure. Yet the pronounced inefficiency observed during the 2015 stock-market bubble reveals that market fundamentals can deteriorate sharply when speculative dynamics intensify, challenging the interpretation of China as a fully mature market. Moreover, the markedly asymmetric responses of the CSI 300 compared with other emerging markets, particularly in episodes where China exhibited muted inefficiency while peers experienced pronounced disruptions, lend support to the idea that non-market stabilization mechanisms, including liquidity provision and policy signaling, play a significant role in shaping China's observed efficiency profile.

The last topic of empirical analysis seeks to assess the possible maturation of the markets under study, based on the levels of efficiency observed over time, as well as the response given to different moments of turbulence, which may be a sign of the strengthening of the institutions established in these economies. As the period covers only the last 19 years, the analysis should be carried out from a comparative perspective in relation to the bulk

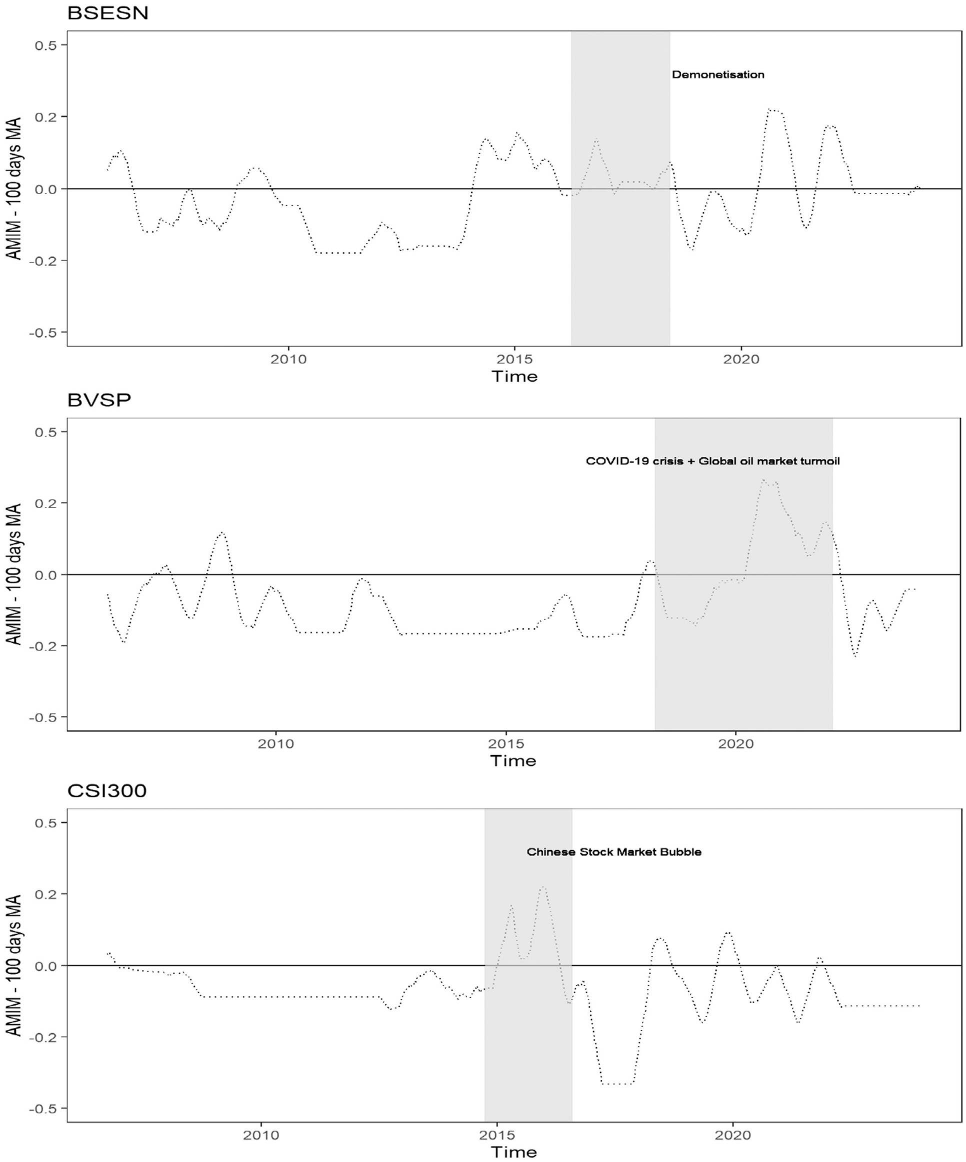

FIGURE 3 | Behavior of the AMIM measure in specific economic events. BSESN (India), BVSP (Brazil), CSI300 (China), JALSH (South Africa), KS11 (South Korea), and TWII (Taiwan). The dotted line represents the 100-day moving average of the AMIM values. Shaded areas comprise, respectively, for India, Brazil, and China, the Demonetization process, the Covid crisis, global oil market turmoil, and the Chinese stock market bubble.

of the literature focused on these markets, where studies covering the last few decades of the last century illustrate inefficient emerging markets as a whole (Claessens et al. 1995; Urrutia 1995; Poshakwale 1996), evidence contrary to that obtained by the method applied, where the markets are essentially characterized as informationally efficient. This paradigm shift coincides with a period in economic history marked by major events (crises, speculative bubbles) such as those mentioned above, which, along with the integration process that has taken place in these economies, may have contributed to strengthening their degree of efficiency, whereas confirming the factors that caused this maturation is beyond the scope of this article.

5 | Conclusion

With the main aim of characterizing the evolution of market efficiency in the context of emerging economies, this paper selected six stock indices representative of this group of economies and computed the AMIM, an emerging efficiency measure in the literature of efficiency in developing markets. This methodological option opened the door to the possibility of analyzing the absolute and relative behavior of the informational efficiency of each of the markets. To our knowledge, this is the first application of this methodology to the study of efficiency in emerging markets. These results are framed in a timeframe that includes important events in the markets on a global scale, which also allowed us to take a preliminary look at the impact that different economic events may have on market efficiency in these economies.

The daily logarithmic returns between 2005 and 2023 were collected from Eikon Datastream to serve as inputs for the empirical method. Based on the autocorrelation coefficients of the observed returns, the outputs obtained result from the consolidation of a raw efficiency measure called MIM, by incorporating the confidence intervals of the autocorrelation coefficients initially obtained.

First, after the interpretative drawbacks found when analyzing the values produced by this efficiency measure, the transition to the more robust AMIM allowed us to obtain a general picture of efficiency levels for the six markets analyzed. The results obtained point to a trend towards informational efficiency in all the markets, evidence that coexists with the presence of moments of inefficiency, supporting the argumentative line of the AMH, which corroborates the dynamic and adaptive nature of the concept of efficiency.

Taking advantage of the possibility of analyzing market efficiency as a relative concept, comparing the evolution of the different indices over the period under analysis revealed different behaviors for each of them, particularly in the context of common economic events. This evidence reinforces the presence of internal dynamics in each of these markets responsible for shaping the evolution of their efficiency levels, which means that it is impossible to characterize this bloc of economies as homogeneous from this point of view.

We then proceeded to identify key moments in the temporal evolution of efficiency levels in each of the indices studied, in an attempt to identify economic events that had an impact from the point of view of market efficiency, both within each of the markets and on a more global scale. The results obtained shed some light on the different degrees of integration in each of the markets, resulting in different impacts on their level of efficiency when major economic events such as the GFC of 2008 and the COVID-19 crisis took place.

In sum, it is possible to conclude that emerging markets present evolutionary dynamics in terms of market efficiency that cannot be captured by a framework as inflexible as the EMH. In turn, the harmonious coexistence of market efficiency with periods marked by high levels of inefficiency positions the AMH as the most appropriate framework for assessing informational efficiency in these markets. The unique nature of each market is also highlighted in this study, establishing the need to consider each economy individually when assessing the level of efficiency of financial markets. The link found between certain economic phenomena and the level of efficiency recorded in the different indices allows us to conclude about the impact and the different reactions of each of the markets to different dynamics in their internal workings, as well as systemic factors. Finally, the results show a process of maturation in these markets, visible in the presence of a frequent state of efficiency throughout the study period, contrary to what has been reported in efficiency studies involving this category of economies in previous periods.

A natural limitation of this study is its insufficiency from the point of view of practical applicability. Recording periods of inefficiency in certain markets during certain time periods does not mean that investors were able to obtain abnormal returns at that time, since a series of other factors, namely the presence of transaction costs, have an impact on the profitability of market operations. The resulting evidence should be cross-checked together with the testing of different trading techniques, to confirm the possibility of taking advantage of reported market inefficiencies.

Another limitation is the short length of the analysis period. Covering only 19 years, the emerging markets analyzed have only seen part of their history studied, removing the possibility of dealing with this concept of efficiency over a longer period, losing the possibility of characterizing past periods of market efficiency, as well as identifying other economic events that have played an important role in the development of the financial markets under analysis. Additionally, we selected six emerging market stock indices, leaving out other relevant countries such as Russia, Indonesia, or Malaysia. Future research should examine additional indices from emerging economies with diverse market characteristics and identify other systemic economic events that affect multiple markets simultaneously, thereby improving the comprehensiveness and representativeness of the analysis.

Finally, a limitation of our approach is the use of a fixed 252-day rolling window. Alternative window lengths may capture turning points more abruptly (shorter windows) or more smoothly (longer windows). Extending the analysis with multiple window sizes represents a promising direction for future research.

For future research, in addition to pursuing more causal inference into market efficiency in these economies, we also believe it would be of the utmost interest to try to align the results produced by this study with other efficiency measures that have already been established or are in the process of being developed. In this way, with the possibility of using a complete portrait of the efficiency of these markets, from the standpoint of the different measures, new insights would flow into this line of literature at a time when it needs to be fed, given the growing need to understand the efficiency dynamics of this group of increasingly relevant economies.

Author Contributions

Júlio Lobão: conceptualization, investigation, methodology, writing – review and editing, project administration, supervision, formal analysis. **Luís Pacheco:** writing – review and editing, formal analysis, supervision, validation, project administration. **Nuno Cruz:** conceptualization, investigation, writing – original draft, methodology, software, data curation.

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Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Disclosure Statement of the Use of AI Tools

The authors declare that AI tools were used solely for language editing purposes.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1]World Economic Outlook, April 2024: Steady but slow: Resilience amid divergence (2024, April 16). IMF.

[2]Key statistics and trends in international trade 2023 (2024, March 26). UNCTAD.

[3]Emerging stock markets are projected to overtake the US by 2030 (2023, June 22). Goldman Sachs.

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