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Evolution of stock market efficiency in Europe: Evidence from measuring periods of inefficiency

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ABSTRACT

This study introduces novel measures to quantify periods of market inefficiency, enabling precise analysis of their evolution over time and effective comparisons across markets or groups of markets. These measures are applied to an extensive dataset comprising stock indices from 25 European countries from 2007 to 2022. The empirical findings reveal a 20% increase in market inefficiency across Europe, primarily driven by heightened average inefficiencies in the stock markets of the group of developed European countries such as Germany and the Scandinavian countries.

1. Introduction

The Efficient Market Hypothesis (EMH), introduced by Fama (1970), is a foundational concept in the field of quantitative finance. The EMH posits that markets are fully informationally efficient, meaning that all relevant information is always correctly reflected in the current price level of a security.

Investigating the validity of EMH is a continuing concern within the academic literature and numerous studies across the globe have painted a complex picture of efficiency in different markets. Sorting this picture, Lim and Brooks (2011) conducted a systematic review of more than 200 studies, observing an increase of methodological approaches focusing on examining variations of market efficiency over time and regions. They explicitly support the notion of evolving market efficiency, which aligns with the framework of Adaptive Market Hypothesis (AMH) in the sense of Lo (2012). Table 1 provides an overview of studies on validating market efficiency across different regions and time periods, along with the methods used therein.

Another noteworthy study is by Tran and Leirvik (2019), which introduced the Adjusted Market Inefficiency Magnitude (AMIM) as a new measure facilitating the comparison of market efficiency across time points and regions. Tran and Leirvik (2019) applied AMIM to the S&P 500 and a U.S. small cap index, concluding that the U.S. stock markets are better characterized by the AMH rather than the EMH.

In this paper, we introduce new measures derived from AMIM. The key novel contribution of our approach lies in quantifying periods of market inefficiency. Unlike conventional approaches that assess only the presence or absence of market efficiency in a predefined period, our measures enable a more precise analysis of market efficiency over time and facilitate effective comparisons

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Table 1
Literature overview. VR-Test: variance ratio test, MVR-Test: multiple variance ratio test, TV-AR model: time varying autoregressive model, SCC-Test: serial correlation coefficient test.

Study	Region	Analyzed period	Methods	Findings
Urquhart and McGroarty (2016)	Global	1990–2014	MVR-Tests	Varying efficiency
Dias et al. (2020)	Global	2019–2020	VR-Test	Mixed results
Ozkan (2021)	Global	2019–2021	MVR-Test	Inefficiency
Jefferis and Smith (2005)	Africa	1990–2001	GARCH approach	Varying efficiency
Huang (1995)	Asia	1988–1992	VR-Test, ADF-Test	Mixed results
Kim and Shamsuddin (2008)	Asia	1990–2005	MVR-Tests	Mixed results, varying efficiency
Smith and Ryoo (2003)	Europe	1991–1998	MVR-Test	Mixed results
Worthington and Higgs (2004)	Europe	1987–2003	VR-Test, MVR-Test, SCC-Test, Runs-Test, uni root Tests	Mixed results
Borges (2010)	Europe	1993–2007	VR-Test, MVR-Tests, Runs-Test	Mixed results
Abraham et al. (2002)	Gulf	1992–1998	VR-Test, Runs-Test	Mixed results
Urrutia (1995)	Latin America	1975–1991	VR-Test, Runs-Test	Mostly inefficient
Grieb and Reyes (1999)	Latin America	1988–1995	VR-Test	Mostly inefficient
Ito and Sugiyama (2009)	U.S.	1955–2006	TV-AR model	Varying efficiency
Lim et al. (2013)	U.S.	1970–2008	Automatic VR-Test, automatic Box–Pierce-Test	Varying efficiency

across markets or groups of markets. Additionally, we contribute to the understanding of the development of stock market efficiency by analyzing an extensive dataset. Specifically, we analyze the most comprehensive European stock market dataset studied to date, covering 25 indices from 2007 to 2022.

The remaining part of the paper proceeds as follows: Section 2 gives a brief review of AMIM and introduces novel measures for analyzing the evolution of market efficiency. Section 3 presents the data and the analytical results, and Section 4 summarizes the main findings of this paper.

2. AMIM and areas of inefficiency

To quantify the level of market efficiency and analyze its variation over time, Tran and Leirvik (2019) introduced the AMIM measure. The authors suggest that AMIM can be interpreted as a test score of the level of market inefficiency.[1] We briefly outline the derivation of AMIM in Section 2.1.

AMIM quantifies the level of market efficiency at specific points in time. However, AMIM is not suitable for comparing periods of inefficiency across markets or analyzing the evolution of such periods over time. To address these limitations, we introduce the novel measures of 'areas of inefficiency' and 'average area of inefficiency' as outlined in Section 2.2. Technically, these measures are straightforward extensions of AMIM, yet they bring great added value for empirical analyses as they enable us investigate periods of inefficiency rather than isolated time points. A comprehensive understanding of periods of inefficiency is crucial, as during such times, price mechanisms in financial markets may not operate efficiently, leading to significant implications for academia, investors, and regulatory bodies.

2.1. AMIM: A measure of market efficiency

The AMIM measure is computed as follows[2]:

Step 1: Conceptually, weak-form EMH is based on an auto-regressive process AR(q)

$$r_t = \alpha + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \cdots + \beta_q r_{t-q} + \epsilon_t \tag{1}$$

[1] More precisely, AMIM refers to the weak-form version of EMH, which states that all historical data is reflected in the current price of a security. We stick with this form of market efficiency in the remainder of this paper.

[2] For a more detailed derivation see Tran and Leirvik (2019).

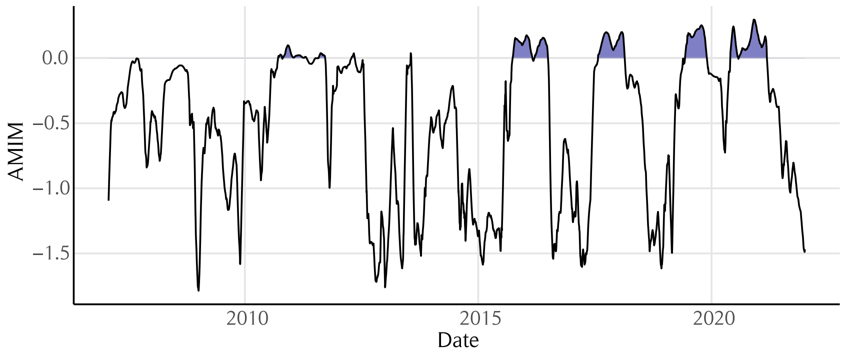

Fig. 1. AMIM measure of Germany (DEU).

and the idea of assuming market efficiency if $\beta_i = 0$, for all $i = 1, \ldots, q$. AMIM seizes upon this and starts with estimating the autocorrelation coefficients $\hat{\beta}$ from Eq. (1). The asymptotic distribution of $\hat{\beta}$ is given by

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

with Σ representing the asymptotic covariance matrix. Next, $\hat{\beta}$ is standardized by multiplying it by the inverse of the triangular matrix L from the Cholesky decomposition $\Sigma = LL'$:

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

Under the null hypothesis of market efficiency, the standardized $\hat{\beta}^{standard}$ follows a normal distribution

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

with I representing the identity matrix.

Step 2: $\hat{\beta}^{standard}$ is used to determine the Market Inefficiency Magnitude (MIM) at time t:

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

where $\hat{\beta}_{j,t}^{standard}$ represents the standardized jth autocorrelation coefficients at time t. MIM values range from 0, indicating a very efficient market, to almost 1, indicating a highly inefficient market.

Step 3: A problem with Eq. (5) is that a greater number of lags q used to estimate β_q in Eq. (1) leads to an increased value of MIM_t indicating a higher degree of market inefficiency when compared to scenarios with fewer lags. To address this issue, 95% confidence intervals for MIM_t for all q are computed under the null hypothesis of efficient markets ($\hat{\beta}^{standard} j, t = 0$ for all j).

Step 4: For a given lag q, R_{CI} represents the range of the confidence interval for MIM_t. Note that, under the null hypothesis, R_{CI} equals the upper limit of the interval. The AMIM at time t is derived from R_{CI} and MIM_t as follows:

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

This construction allows $AMIM_t$ to take on both negative and positive values of less than one. By design, AMIM is greater than 0 when MIM_t is outside of the 95% confidence interval. Consequently, Tran and Leirvik (2019) consider markets as inefficient whenever $AMIM > 0$ and interpreted markets as more inefficient when $AMIM_t$ increases.

2.2. Areas of inefficiency: A measure of the magnitude and the evolution of market inefficiencies

In this section, we describe the process of developing areas of inefficiency and the average area of inefficiency as novel measures for analyzing the evolution of market inefficiencies. The process begins with the calculation of AMIM using a daily rolling window approach with a one-year window length. We determine the optimal lag length q for each observation window using the Akaike Information Criterion (AIC). If the AIC suggests an AR(0) model as the best fit, we select the second-best fitted AR(q) model suggested by the AIC to ensure our assessment of market efficiency at time t is consistently based on AMIM.

We apply a 30-day moving average approach to smoothen the data. Fig. 1 illustrates the 30-day moving average AMIM values for Germany (DEU) from 2007 to 2022. This figure underscores the challenges in evaluating the evolution of market inefficiency using the AMIM measure, as it lacks a quantification of the magnitudes of periods of inefficiency.

As inefficiency at time t occurs when $AMIM_t > 0$, and longer periods of positive AMIM as well as higher values of $AMIM_t$ indicate greater inefficiency, the area between the AMIM graph and the x-axis can be considered as a measure of the magnitude of a period of inefficiency. We formalize this concept in Definitions 1 and 2.

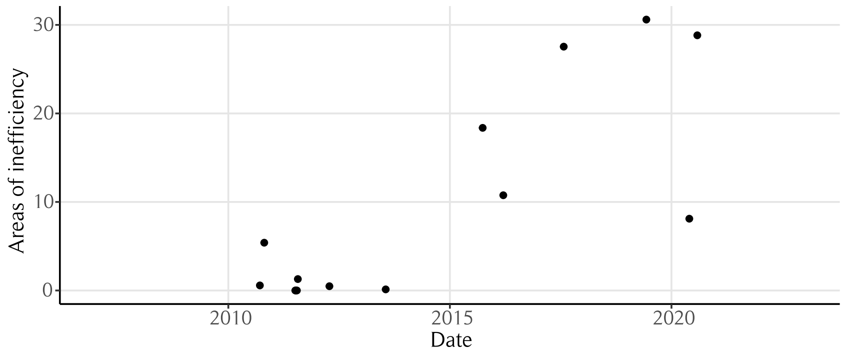

Fig. 2. Areas of inefficiency of Germany (DEU).

Definition 1. For a given time period I, a period of inefficiency P is defined as

$$P = [s, e] \cap I, \tag{7}$$

where s is the smallest point in I and e is the largest point in I such that $AMIM_t > 0$ for all $t \in P$.

Definition 2. If there are k periods of inefficiency $P_1, \dots, P_k$ in a given time period I, we define the i$^{\text{th}}$ area of inefficiency A_i as:

$$A_i = \sum_{t \in P_i} AMIM_t, \quad i = 1, \dots, k. \tag{8}$$

A_i provides us with an understanding of the magnitudes of a country's periods of inefficiency over time, as illustrated in Fig. 2 for Germany from 2007 to 2022.

The key benefit of A_i is quantifying the evolution of market inefficiencies, achieved by comparing A_i across various time periods. The informative quality of such an analysis can be enhanced by considering the average area of inefficiency, a concept formalized in Definition 3.

Definition 3. For a given time period I, we define the average area of inefficiency AA_I as:

$$AA_I = \frac{1}{|I|} \sum_{\{i:\ s_i \in I,\ e_i \in I\}} A_i, \tag{9}$$

where $|I|$ denotes the length of the time period I, and s_i and e_i are the points that define P_i as per Definition 1.

AA_I fulfills additivity for multiple time periods and multiple assets, as outlined in Propositions 1 and 2.

Proposition 1. *For n disjoint time periods $I_i, \dots, I_n$: $AA_{\cup_i I_i} = \sum_{i=1,\dots,n} \frac{|I_i|}{|I_1|+\cdots+|I_n|} AA_{I_i}$*

Proof. The proof follows from the definition of AA_I. $\square$

Proposition 2. *For a given time period I and n assets: $\sum_{i=1}^{n} AA_I^i = AA_I^{1,\dots,n}$, where $AA_I^{1,\dots,n}$ denotes the average area of inefficiency of all n assets combined.*

Proof. The proof follows from the definition of AA_I. $\square$

AA_I is defined to be interpreted as an annualized value. This means that AA_I can be used to analyze the evolution of market efficiency between time periods of equal or different lengths.

3. Data and analytical results

In the empirical exercise in Sections 3.1 and 3.2, we compute the average areas of inefficiency using an extensive data set of 25 European stock market indices from 2007-01-01 to 2022-12-31. Subsequently, we investigate the evolution of these values over time, differentiating between developed, emerging, and frontier markets. Finally, in Section 3.3, we conduct simulation-based analyses to contextualize the empirical results and to further validate the effectiveness of A_I and AA_I.

Table 2
Data overview.

Country	RIC	Index	Currency	MSCI cl.
AUT	.ATX	VIENNA SE AUSTRIAN TRADED IDX Index	EUR	Developed
BEL	.BFX	BEL 20 Index	EUR	Developed
CHE	.SSMI	Swiss Market Index	CHF	Developed
DEU	.GDAXI	DAX Index	EUR	Developed
DNK	.OMXC20	OMX Copenhagen 20 Index	DKK	Developed
ESP	.IBEX	IBEX 35 Index	EUR	Developed
FIN	.OMXH25	HEX25 INDEX	EUR	Developed
FRA	.FCHI	CAC 40 Index	EUR	Developed
GBR	.FTSE	FTSE 100 Index	GBP	Developed
IRL	.ISEQ	ISEQ Overall Price Index	EUR	Developed
ITA	.FTMIB	FTSE MIB IDX	EUR	Developed
NLD	.AEX	Amsterdam Exchanges Index	EUR	Developed
NOR	.OBX	OBX INDEX	NOK	Developed
POR	.PSI20	EURONEXT LISBON PSI INDEX	EUR	Developed
SWE	.OMXS30	STO OMX INDEX	SEK	Developed
CZE	.PX	PX-PRAGUE SE IND IDX	CZK	Emerging
GRC	.ATG	ATHEX COMPOSITE SHARE PRICE INDEX	EUR	Emerging
HUN	.BUX	BUDAPEST SE IDX	HUF	Emerging
POL	.WIG20	WIG20 INDEX	PLN	Emerging
TUR	.XU100	ISE National Index	TRY	Emerging
EST	.OMXTGI	OMXT GENERAL	EUR	Frontier
HRV	.CRBEX	CROBEX IDX	EUR	Frontier
ISL	.OMXIPI	OMX ICELAND ALL SHARE PI	ISK	Frontier
LTU	.OMXVGI	OMXV GENERAL	EUR	Frontier
ROU	.BETI	BUCHAREST SE IDX	RON	Frontier

3.1. Data

Our empirical analysis is based on 25 European stock market indices. We specifically selected this dataset because Europe is a diverse yet cohesive region. Analyzing this data can provide insights into various economies and financial systems, offering valuable implications for a broad readership. The selected indices represent a range of countries classified by MSCI (MSCI, 2022) into 'Developed', 'Emerging', and 'Frontier' markets. Specifically, we examine the market indices listed in Table 2 from 2007 to 2022.

The raw data consists of daily stock market returns from Refinitiv, which are subsequently converted into continuous returns.

3.2. Empirical results

The average areas of inefficiency AA_I are computed for all 25 countries for the time periods $I_1 = [2007, 2014]$ and $I_2 = [2015, 2022]$. The results of this computation are presented in Table 3. As shown in Proposition 2, we can add up AA_I values of countries and thereby get the average area of inefficiency for all developed, or all emerging, or all frontier European markets. These combined AA_I values are shown in the last rows in Table 3. When comparing the average areas of inefficiency between I_1 and I_2 across all countries, we observe an increase of 20%. Notably, inefficiency within the developed markets increased by 32%. In contrast, emerging and frontier markets experienced more modest increases in inefficiency, with 3% for emerging and 10% for frontier markets.

Fig. 3 depicts the evolution of average inefficiencies in developed markets. Among the 15 developed markets, 10 experienced an increase in inefficiency, while only 5 showed improvements in efficiency. Notably, DEU, the most efficient market in I_1, experienced the largest increase in inefficiency of +14.58. Conversely, ITA achieved the largest decrease in inefficiency of −6.07, becoming the least inefficient market in I_2. Overall, the AA_I for this group increased from 110.74 to 146.42.

Fig. 4 illustrates the evolution of average inefficiencies in emerging markets. A notable trend is the decreasing market inefficiency in all countries except GRC. Despite being the most inefficient market in I_1 with $AA_{I_1} = 21.00$, GRC experiences a further 43% increase in inefficiency to $AA_{I_2} = 29.97$. This positions GRC as the most inefficient European stock market in I_2. The overall increase in inefficiency among emerging markets can be attributed solely to the rise in inefficiency observed in GRC.

Fig. 5 displays the evolution of average inefficiencies in frontier markets, revealing two distinct trends. There is a strong increase in inefficiency in HRV, EST, and LTU, totaling an increase of 25.95. Consequently, HRV and EST become the most inefficient European markets in I_2, following GRC. In contrast, ISL and ROU show a substantial decrease in inefficiency, leading to a combined decrease of −21.39.

Given that larger AA_I values indicate greater market inefficiency, we can also use AA_I to systematically rank countries based on their inefficiency levels. Table 4 provides a ranking of European stock markets, from the least inefficient to the most inefficient, for the time periods $I_1 = [2007, 2014]$ and $I_2 = [2015, 2022]$.

Table 3
Average areas of inefficiency per country.

Country	$AA_{[2007,\ 2014]}$	$AA_{[2015,\ 2022]}$	Change
AUT	7.44	11.03	48%
BEL	7.38	13.43	82%
CHE	8.21	5.28	−36%
DEU	0.98	15.53	1479%
DNK	4.75	9.59	102%
ESP	8.40	12.73	52%
FIN	2.21	2.91	32%
FRA	10.63	5.42	−49%
GBR	13.23	13.28	0%
IRL	10.20	7.48	−27%
ITA	6.65	0.58	−91%
NLD	2.38	8.23	245%
NOR	5.81	11.99	106%
POR	14.42	14.15	−2%
SWE	8.05	14.81	84%
CZE	5.87	1.38	−77%
GRC	21.00	29.97	43%
HUN	7.55	6.79	−10%
POL	8.88	7.55	−15%
TUR	5.52	4.36	−21%
EST	9.58	15.53	62%
HRV	5.00	21.08	321%
ISL	15.55	7.30	−53%
LTU	2.66	6.59	148%
ROU	13.92	0.78	−94%
All developed	110.74	146.42	32%
All emerging	48.83	50.07	3%
All frontier	46.71	51.27	10%
All countries	206.27	247.76	20%

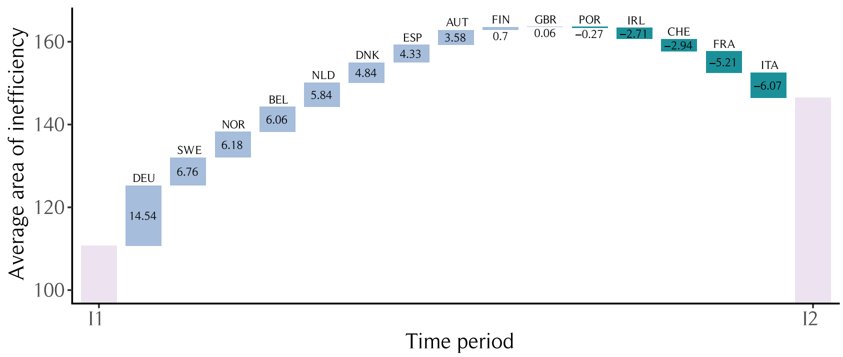

Fig. 3. Evolution of average areas of inefficiency for developed markets.

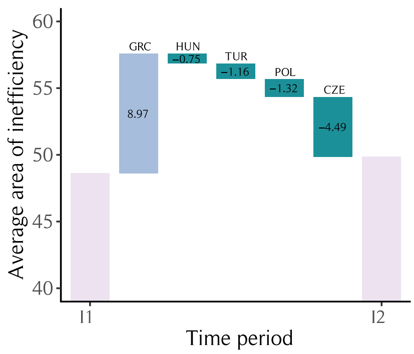

Fig. 4. Evolution of average areas of inefficiency for emerging markets.

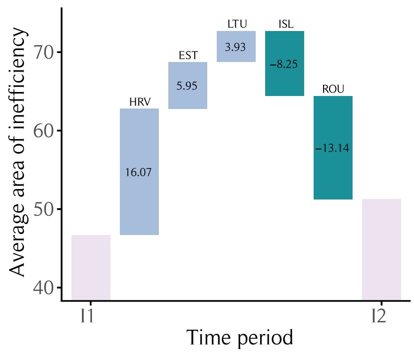

Fig. 5. Evolution of average areas of inefficiency for frontier markets.

Table 4
Efficiency ranking by AA_I.

	$I1$		$I2$		Absolute change	
Rank	Country	AA_I	Country	AA_I	Country	AA_I
1	DEU	0.98	ITA	0.58	ROU	−13.14
2	FIN	2.21	ROU	0.78	ISL	−8.25
3	NLD	2.38	CZE	1.38	ITA	−6.07
4	LTU	2.66	FIN	2.91	FRA	−5.21
5	DNK	4.75	TUR	4.36	CZE	−4.49
6	HRV	5.00	CHE	5.28	CHE	−2.94
7	TUR	5.52	FRA	5.42	IRL	−2.71
8	NOR	5.81	LTU	6.59	POL	−1.32
9	CZE	5.87	HUN	6.79	TUR	−1.16
10	ITA	6.65	ISL	7.30	HUN	−0.75
11	BEL	7.38	IRL	7.48	POR	−0.27
12	AUT	7.44	POL	7.56	GBR	0.06
13	HUN	7.55	NLD	8.23	FIN	0.70
14	SWE	8.05	DNK	9.59	AUT	3.58
15	CHE	8.21	AUT	11.02	LTU	3.93
16	ESP	8.40	NOR	11.99	ESP	4.33
17	POL	8.88	ESP	12.73	DNK	4.84
18	EST	9.58	GBR	13.28	NLD	5.84
19	IRL	10.20	BEL	13.43	EST	5.95
20	FRA	10.63	POR	14.15	BEL	6.06
21	GBR	13.23	SWE	14.81	NOR	6.18
22	ROU	13.92	DEU	15.53	SWE	6.76
23	POR	14.42	EST	15.53	GRC	8.97
24	ISL	15.55	HRV	21.08	DEU	14.54
25	GRC	21.00	GRC	29.97	HRV	16.07

Developed, Emerging, Frontier.

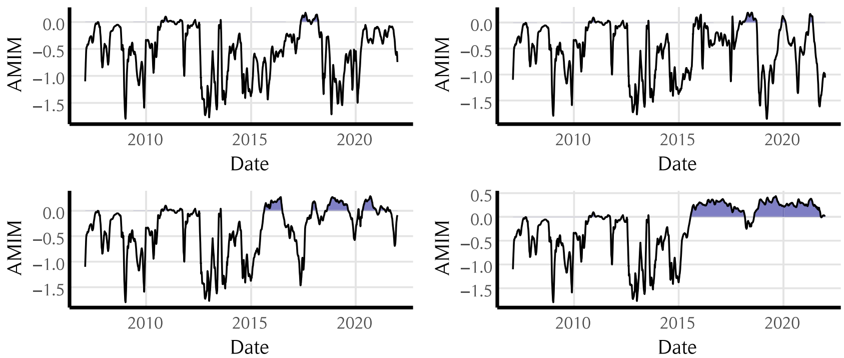

Fig. 6. AMIM measures for Germany (DEU). Top left: GBM, Top right: MR with $\alpha = 0$, Bottom left: MR with $\alpha = 0.1$, Bottom right: MR with $\alpha = 0.2$.

3.3. Simulations

In this section, we analyze stylized simulated stock index prices for Germany (DEU) in the period $I_2 = [2015,\ 2022]$. Simulation methods include a geometric Brownian motion (GBM) process[3] and mean reversion (MR) processes[4] with varying strengths of mean reversion.

Fig. 6 displays AMIM measures for the different simulation methods. We observe only few inefficiencies for the GBM process, while the MR processes exhibit larger periods of inefficiency with increasing strength α.

Fig. 7 illustrates areas of inefficiency A_i for the different methods. Actual A_i in I_2 (•) are notably larger than the A_i of a GBM process (∘), falling between the A_i of an MR process with $\alpha = 0$ (+) and $\alpha = 0.1$ (×). We can quantify this observation and contextualize all empirically found average inefficiencies by comparing the real values from Table 3 with the AA_{I_2} values of the different simulation methods in Table 5.

[3] The GBM process is defined as $dS_t = \mu S_t dt + \sigma S_t dW_t$, where S_0 is the last price of DEU in I_1, μ and σ are the mean and volatility of the returns of DEU in I_1, and W_t is a Wiener process.

[4] The MR process is defined as $S_t = S_{t-1} + \alpha(\overline{S}_t - S_{t-1}) + \epsilon_t$, where S_0 is the last price of DEU in I_1, $\alpha > 0$ is the strength of mean reversion, $\overline{S}_t$ is the mean of the previous 10 prices, and $\epsilon_t \sim \mathcal{N}(0, \overline{\sigma})$ is a random price move at t with $\overline{\sigma}$ set as the volatility of the price changes of DEU in I_1.

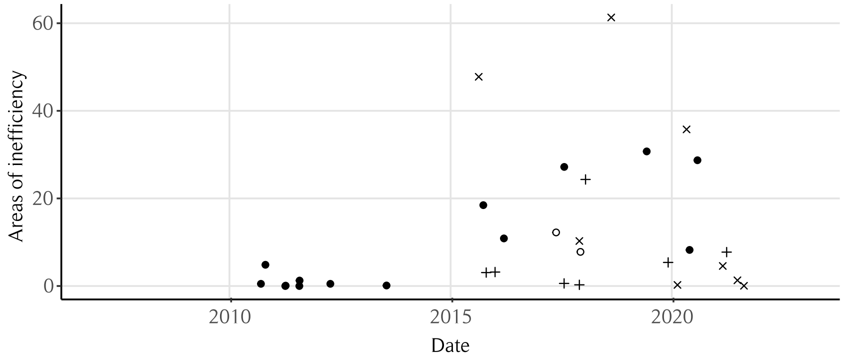

Fig. 7. Areas of inefficiency for Germany (DEU). •: Real, ∘: GBM, +: MR with $\alpha = 0$, ×: MR with $\alpha = 0.1$.

Table 5
Average areas of inefficiency for simulated Germany (DEU).

Country	$AA_{[2007,\ 2014]}$	$AA_{[2015,\ 2022]}$	Change
DEU (GBM)	0.98	2.50	155%
DEU (MR with $\alpha = 0$)	0.98	5.57	468%
DEU (MR with $\alpha = 0.1$)	0.98	20.16	1957%
DEU (MR with $\alpha = 0.2$)	0.98	69.40	6982%

4. Conclusion

The first aim of this study was to extend the AMIM measure to facilitate the quantification of magnitudes of periods of inefficiency, enable the comparison of such periods across regions, and analyze the evolution of market inefficiency over time.

The second aim of this study was to investigate the evolution of market efficiency across a representative dataset. The findings of an empirical analysis of the stock indices of 25 European countries from 2007 to 2022 suggest that, overall, inefficiency in Europe increased by 20%. This increase is predominantly attributed to a 32% rise in inefficiency in the stock markets of developed European countries. Specifically, we observe substantial increases in Germany (+1479%) and the Scandinavian countries (NOR: +106%, DNK: +102%, and SWE: +84%), while other developed European countries experienced decreases in stock market inefficiency.

CRediT authorship contribution statement

J. Bock: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Conceptualization. **S. Geissel:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Conceptualization.

Data availability

Data will be made available on request.

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