Analysing Similarities between Dot-Com and Green Economy Bubbles: A Dynamic Time Warping Approach to the Euphoria Phase

Abstract: This article examines three groups of indices representing the green economy sector to identify the presence in their quotations of the euphoria phase which is characteristic for price bubbles. The indices were analysed by market type, geographic region and sector. The study was conducted on 31 indices from the NASDAQ OMX Green Economy from September 1, 2005 to April 8, 2024. The dynamic time warping method was used for the analysis.

The conclusions include the finding that the green economy market is not currently in the euphoria phase. The COVID-19 pandemic caused 20 out of the 31 analysed indices to enter the euphoria phase, leading to significant increases in green economy indices. Furthermore, the effectiveness of the dynamic time warping method in determining the end of the euphoria phase was demonstrated. The average return 30 days after the end of the euphoria phase was -8.8%.

Key words: price bubbles, euphoria, dynamic time warping, green bubble

Classification codes: E3; G11; G12

1. Introduction

Emerging price bubbles in capital markets, which burst unexpectedly, cause numerous consequences. These range from small-scale effects, such as negative welfare effects (Su et al., 2020), to triggering severe financial crises with significant macroeconomic consequences (Brunnermeier et al., 2020; Jarrow & Lamichhane, 2021). Examples of such financial crises linked to earlier price bubble formations include Japan's asset price bubble of the 1980s-90s (Hu & Oxley, 2018), the dot-com bubble (Morris & Alam, 2012), and the Global Financial Crisis of 2008 (Cheema et al., 2022). All these crises were preceded by the formation of price bubbles in specific market segments, such as technology companies or real estate, and the bursting of these bubbles led to serious macroeconomic consequences for the global economy. Not all crises are preceded by the occurrence of price bubbles, but extraordinary market situations can paradoxically contribute to their formation. Examples include the COVID-19 pandemic of 2020 and the full-scale aggression of Russia against Ukraine in 2022. These events led to numerous changes in investment markets, causing price bubbles in capital markets, commodities and cryptocurrencies (Gharib et al., 2021; Guo et al., 2022; Lei et al., 2023).

Due to the increasing frequency of price bubbles in various markets and the consequences they bring, it has become crucial to develop a procedure that will warn about a currently forming price bubble in a given market and the end of the so-called euphoria phase, after which a market collapse and a

significant price drop occur. The occurrence of the euphoria phase in the market is associated with irrational investing (Baker & Ricciardi, 2014; Hirshleifer, Subrahmanyam & Titman, 2006), and creating a mechanism to warn against such investor behaviour is the goal of this study. This research objective was undertaken using the example of the green economy market, which has enjoyed unwavering interest from investors in recent years (Basse et al., 2023; Madaleno et al., 2022). There are indications that in the coming years, solutions and companies from the green economy sector, alongside the AI sector, will be a major area of interest for investors, potentially leading to new price bubbles in these market segments (Bonaparte, 2024). Therefore, this article is mainly directed at both individual and institutional investors, as well as market analysts and market regulators.

The paper contributes to the literature in two aspects. First, it assesses whether the current green economy market is in a phase comparable to the euphoria phase characteristic of price bubbles. Secondly, it identifies the sub-period when this market was closest to such a phase, from September 1, 2005 to April 8, 2024. These studies were conducted using the DTW (dynamic time warping) method (Giorgino, 2009) for indices from the green economy sector provided by the NASDAQ stock exchange. All examined indices belong to the NASDAQ OMX Green Economy Index Family, and for the purposes of the study, these indices were analysed in three research dimensions: for the main market divided into overarching categories such as SOLAR, WIND and GLOBAL WATER, by geographic regions and by sectoral division. Thirdly, it demonstrates the feasibility of using the DTW procedure to detect the euphoria phase in investment markets.

In the following section, a literature review concerning the green economy segment is presented, followed by a discussion of the applied methodology and the data used. The fourth section describes the obtained research results, and then the final conclusions are presented.

2. Literature review

The green economy market, the subject of this study, is gaining significance in the context of emerging research and reports on climate change and human CO2 emissions. Examples of actions aimed at mitigating climate change by influencing changes in corporate operations include agreements such as the Paris Agreement signed in 2015, the Glasgow Climate Pact from 2021 (Demiralay et al., 2023; Hassan, 2022) and the European Green Deal from 2023. The discussion on human-induced climate changes, supported by appropriate provisions in international agreements designed to counteract negative climate changes, has contributed to the emergence of a trend in economics known as the green economy (Wang et al., 2021). This trend is associated with easier access to funding for companies considered to belong to the green economy sector, where sustainable development is fundamental to their operations (Abu-Ghunmi et al., 2023). Some companies are so eager to show

investors that they belong to this sector that there is even talk of the phenomenon of "painted green" (Demidov, 2022) or greenwashing (Fella & Bausa, 2024). Therefore, the main studies concerning the green economy sector, focusing on the formation of price bubbles and the sector's connections with other markets such as the oil or gold markets, are presented below.

The persistent trend of "being green" over the years has led to a significant inflow of capital into companies representing this market. Hence, it is necessary to investigate whether the green economy market is currently or has been in the past in a phase that can be called the euphoria phase, characteristic of a price bubble. Previous studies show that concerns regarding the formation of such a price bubble in the green economy market are justified (Lehnert, 2022). Similar conclusions are reached by the authors of the study (Basse et al., 2023), who state that the green economy market, represented by the NASDAQ OMX Green Economy Index and the MSCI World Equity Index, experiences periods that can be described as price bubbles. Moreover, for these indices, one can speak of the coexistence of such periods. As an index that behaves differently, however the authors point to the MVIS Global Coal Index.

In another study (Demiralay et al., 2023), it is demonstrated that the green economy market is large enough to warrant analysis from the perspective of individual sectors, each possessing distinct risk-return characteristics. Furthermore, this study indicates an increase in both risk and return during the COVID-19 pandemic. The authors also highlight that, compared to traditional (non-green) sectors, companies in the green economy sector exhibit higher investment efficiency. The positive impact on the valuations of companies in the green economy sector due to the outbreak of the COVID-19 pandemic was also noted in the work of Zeng et al. (2023). This study also points out that the NASDAQ OMX Bio/Clean Fuels Index and the NASDAQ OMX Geothermal Index contribute to increased risk in the agricultural commodities market, specifically grain commodities. At the same time, the WilderHill Clean Energy Index and the NASDAQ OMX Wind Energy Index can be defined as markets receiving investment risk from other segments.

The dependence of the green economy market on carbon prices is highlighted in the work of Hassan (2022). This study shows that carbon prices significantly impact the volatility of green economy sector markets. On the other hand, regional connections of green economy markets are indicated by Gunay et al. (2022). The conclusions drawn from their study are as follows. First, the authors note weakening connections between green economy markets in the USA and Europe and growing connections between the USA and Asia over the years. Additionally, they point to the connections of green economy markets in these three regions with oil and gold prices. This study found that oil prices contribute to increased risk in the green economy sectors for the USA and Europe due to the COVID-

19 pandemic, while for the green economy market in Asia, this pattern was confirmed over the long term.

The conclusions from the study by Song and Hua (2024) are also intriguing. The authors analysed the development of the green economy sector in BRICS countries. This study is noteworthy because BRICS countries, as the authors state, have certain technological and infrastructural backlogs and are perceived as places where implementing the green economy is more challenging. This is linked to the pressure from these societies for continuous and dynamic economic growth, which is easier and cheaper to achieve in the short term using solutions not aligned with the green economy. However, the researchers point out that only sustainable changes in production and consumption can significantly influence the development of the green economy sector in these countries. The study also highlights the leading role of administrative solutions that should promote the development of renewable energy sources and technological innovations as the main drivers of the green economy. This latter point is also emphasised in the work of Xu and Li (2024).

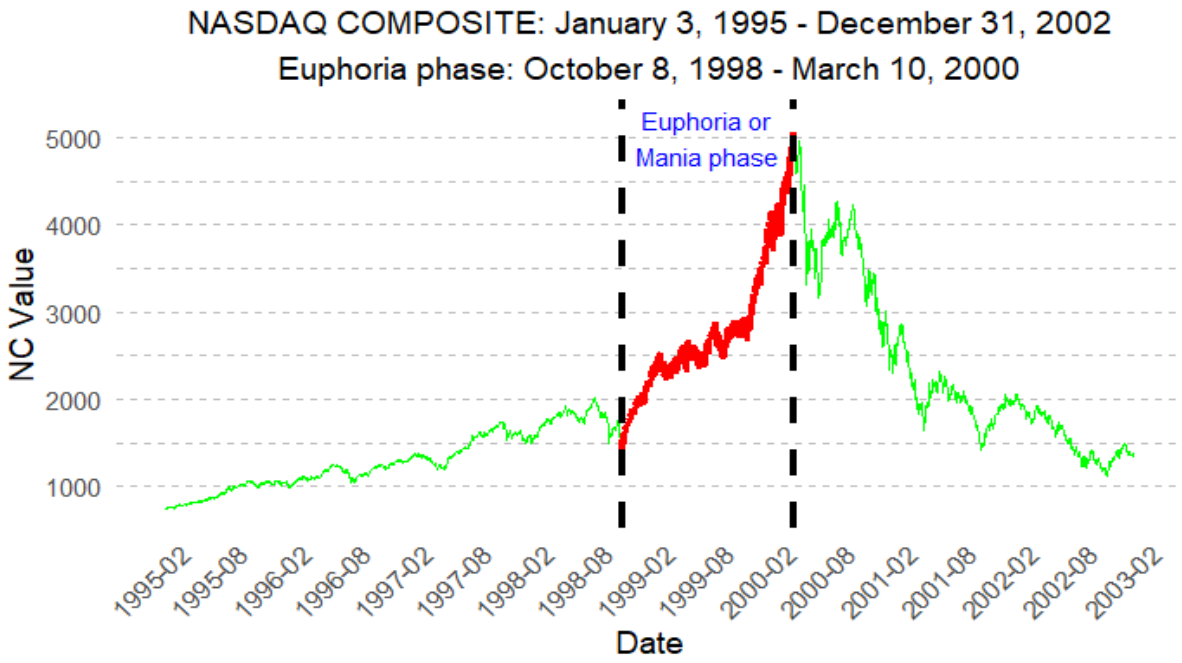
The work of Qadri et al. (2024) highlights significant directions of scientific research dedicated to green economy issues. Among the most frequently addressed topics in scientific research in this area, the authors identify energy efficiency, reduction in carbon emissions, technological innovations and a focus on the circular economy. Moreover, the authors predict the systematic growth and development of the green economy sector and green finance in the future. This is also emphasised in the study by Yuyang (2024).

The cited examples of recent scientific research in the area of green finance clearly indicate the need to verify whether a price bubble is currently forming in this market or whether one was already present in the past. Therefore, the decision was made to conduct the following study, which aims to provide answers to these defined research questions.

3. Methodology and data

The study utilised data obtained from the website indexes.nasdaqomx.com. A total of 31 indices belonging to the "NASDAQ OMX Green Economy Index Family" were examined, along with the quotations for the NASDAQ COMPOSITE (NC) index, which were obtained from the website https://fred.stlouisfed.org/series/NASDAQCOM. The quotations for the NC index were used as a benchmark to define the euphoria phase that occurs immediately before the bursting of a price bubble. The quotations for the NC index during the price bubble, along with the highlighted euphoria period, are presented in Figure 1.

Figure 1 Dot-Com Bubble with highlighted euphoria phase



Source: Own study.

Figure 1 illustrates the quotations of the NC index during the price bubble period, with the euphoria phase marked, after which the index quotations collapsed. The beginning and end of the bubble period were determined based on the studies of Morris & Alam (2012) and Siegel (2003). Additionally, both the selection of the period for the bubble and the definition of the beginning and end of the euphoria phase were influenced by theoretical works (Kindleberger & Bernstein, 2002; Minsky, 1972). During the euphoria phase, the index quotations increased by 255.8% from 1419.12 to 5048.62 points. Following the end of the euphoria phase, the index lost 5% after 5 trading days (March 17, 2000), 11.9% after 20 trading days (April 7, 2000) and more than 31% after 30 trading days (April 24, 2000).

The indices compared with the NC index during the euphoria phase are part of the broadly defined market known as the green economy. For these indices, representing the three previously defined segments of this market, Table 1 contains basic descriptive statistics determined for the logarithmic returns over the period from September 1, 2005 to April 8, 2024. The start of the study period is defined by the availability of data provided by NASDAQ. Daily data were used in the study as, noted in Demiralay et al. (2021), daily data is a better choice than weekly or monthly data.

Table 1 Selected descriptive statistics for the analysed green economy indices

Group	Index	Mean	Median	Standard Deviation	Kurtosis	Skew.	Range	Min	Max
Main group of indices	Green Economy	0.03%	0.09%	0.013	8.932	-0.560	22.80%	-12.20%	10.50%
	SOLAR	0.02%	0.07%	0.023	6.248	-0.467	35.20%	-19.30%	15.90%
	GLOBAL WATER	0.02%	0.08%	0.012	9.835	-0.469	22.00%	-10.90%	11.10%
	WIND	0.02%	0.06%	0.019	8.543	-0.464	33.30%	-17.50%	15.90%
Regional indices	GE ASIA	-0.01%	0.04%	0.012	4.160	-0.366	17.80%	-10.10%	7.80%
	GE EUROPE	0.02%	0.08%	0.015	9.231	-0.446	26.20%	-14.70%	11.50%
	GE USA	0.04%	0.10%	0.015	7.619	-0.409	23.40%	-12.20%	11.10%
	GE without USA	0.02%	0.07%	0.013	9.622	-0.588	23.00%	-13.10%	9.90%
	CE ASIA	0.00%	0.04%	0.018	4.562	-0.241	25.40%	-11.20%	14.20%
	CE EUROPE	0.02%	0.10%	0.017	9.410	-0.438	28.20%	-14.40%	13.80%
	CE USA	0.04%	0.10%	0.015	7.594	-0.310	24.80%	-12.30%	12.50%
	CE without USA	0.02%	0.09%	0.015	11.709	-0.624	28.20%	-14.10%	14.10%
Sectoral indices	ADVANCED MATERIALS	0.02%	0.06%	0.017	6.004	-0.200	25.40%	-12.10%	13.30%
	BIO /CLEAN FUELS	-0.01%	0.05%	0.023	7.678	-0.385	34.10%	-18.20%	15.90%
	CLEAN ENERGY	0.03%	0.08%	0.014	10.511	-0.474	26.50%	-13.10%	13.50%
	DEVELOPER /OPERATOR	0.01%	0.07%	0.012	16.152	-0.905	28.60%	-16.50%	12.10%
	ENERGY MANAGEMENT	0.04%	0.06%	0.016	8.140	-0.304	27.90%	-13.90%	14.00%
	ENERGY STORAGE	0.02%	0.05%	0.018	4.940	-0.185	27.70%	-12.80%	14.80%
	ENRGY EFFICIENCY	0.04%	0.07%	0.014	7.429	-0.279	24.50%	-12.20%	12.30%
	FUEL CELL	-0.04%	-0.10%	0.033	4.792	0.283	42.40%	-20.70%	21.60%
	GEOTHERMAL	0.00%	0.06%	0.018	8.331	0.037	31.60%	-13.40%	18.30%
	GREEN BUILDING	0.01%	0.06%	0.016	12.984	-0.915	27.60%	-17.10%	10.50%
	GREEN IT	0.03%	0.06%	0.016	7.019	-0.178	23.30%	-10.70%	12.60%
	HEALTHY LIVING	0.03%	0.07%	0.013	7.141	-0.248	21.60%	-11.10%	10.40%
	LIGHTING	0.02%	0.05%	0.018	5.185	-0.340	25.70%	-14.90%	10.80%
	NATURAL RESOURCES	0.04%	0.08%	0.019	24.460	-1.466	45.70%	-31.90%	13.80%
	POLLUTION MITIGATION	0.03%	0.04%	0.013	6.630	-0.421	21.50%	-12.70%	8.70%
	RECYCLING	0.04%	0.11%	0.014	6.847	-0.584	22.80%	-11.90%	10.90%
	RENEWABLE ENERGY	0.02%	0.08%	0.015	11.824	-0.717	29.40%	-15.30%	14.10%
	SMART GRID	0.05%	0.09%	0.015	6.913	-0.422	28.00%	-15.00%	13.10%
	TRANSPORTATION	0.05%	0.10%	0.016	6.757	-0.372	25.10%	-13.70%	11.40%

Source: Own study.

The data in Table 1 comprise basic descriptive statistics divided into three main research segments: the main index along with the primary market categories, geographic divisions and individual sectors of the green economy market. The descriptive statistics were calculated for logarithmic returns based on 4693 observations for each of the 31 data series studied.

Based on the average rate of return, it can be observed that for three indices, namely FUEL CELL, BIO/CLEAN FUELS and GE ASIA, negative average returns were recorded at -0.04%, -0.01% and -0.01%, respectively. Interestingly, the five highest average returns, above 0.039%, were achieved by indices

from the group of sectoral indices: ENERGY EFFICIENCY, RECYCLING, NATURAL RESOURCES, SMART GRID and TRANSPORTATION. This illustrates the significant range of results within this group, as the two lowest values were also achieved by indices from the sectoral indices group. In terms of standard deviation, the highest investment risk is associated with the two indices with the lowest returns, BIO/CLEAN FUELS and FUEL CELL. For these investments, risks were recorded at 2.3 and 3.3 percentage points respectively, indicating the low investment efficiency of these two sectors compared to the other studied indices. Besides these indices, high investment risk, measured by the standard deviation of the return rate, was also noted for two of the main indices, WIND and SOLAR, as well as the NATURAL RESOURCES index, which had one of the highest average returns. The skewness values indicate that the return rate distributions of all indices studied (except GEOTHERMAL and FUEL CELL) are left-skewed. The kurtosis values indicate that returns are leptokurtic. The remaining columns present the range and the minimum and maximum observed rates of return.

As previously indicated, the study employed the dynamic time warping (DTW) methodology to compare each of the identified sub-periods for each data series with the template representing the euphoria phase during the dot-com bubble. The result of this comparison is the calculated standardised minimum alignment value, defined for each series as ϕ (Giorgino, 2009):

$$D(\mathrm{X},\mathrm{Y}) = \min_{\varphi} d_{\varphi}(X,Y) \qquad (1)$$

where:

X – time series for a studied index, $X = X_i = (x_1, \ldots, x_N)$,

Y – pattern time series (euphoria phase for NASDAQ COMPOSITE index), $Y = Y_j = (y_1, \ldots, y_M)$.

To receive the optimal alignment value, the local dissimilarity function is defined between any pair of elements x_i and y_j in this way:

$$d(i,j) = f(x_i, y_j) \geq 0 \qquad (2)$$

which is the input for the warping curve $\varphi(\mathrm{k}), \mathrm{k} = 1, \ldots, \mathrm{T}$:

$$\varphi(\mathrm{k}) = (\varphi_x(k), \varphi_y(k)) \qquad \text{with}$$

$$\varphi_x(k) \in \{1, \ldots, N\}, \qquad (3)$$

$$\varphi_y(k) \in \{1, \ldots, M\}. \qquad (4)$$

Based on this, the average accumulated distortion between the analysed time series is possible to calculate:

$$d_{\varphi}(X,Y) = \sum_{k=1}^{T} d\,(\varphi_x(k), \varphi_y(k)) m_{\varphi}(k) / M_{\varphi} \qquad (5)$$

where:

$m_{\varphi}(k)$ – per-step weighting coefficient,

M_φ – corresponding normalisation constant.

From that, the minimal alignment can be obtained considering user-defined constraints, for example, boundary conditions, continuity, or monotonicity (Keogh & Ratanamahatana, 2005). The lower the alignment value, the better the tested time series is adjusted to the adopted pattern. For example, if a fragment of the pattern is compared with the pattern itself, the distance value is 0. It can also be said that each local stretch or compression of the studied time series for an index to fit the benchmark incurs a bigger penalty, resulting in a higher minimum alignment value. All calculations were performed using the R language, specifically, the DTW package (Giorgino, 2009).

4. Research results

a. Results for major market indices

Table 2 presents the results of the obtained minimal distance, representing the optimal fit to the pattern, as well as the start and end for this sub-period. Additionally, the last column provides the value of the normalised distance for the last analysed sub-period for each index, allowing for the assessment of whether the current green economy market can be described as experiencing a period resembling the euphoric phase characteristic of a price bubble.

Table 2 Best and last match for the main group of indices

		Best match			Last match
No.	Index name	Minimal normalised distance	Start date	End date	Normalised distance
1	Green Economy	0.145	23.03.2020	30.08.2021	0.814
2	SOLAR	0.108	23.03.2020	30.08.2021	1.139
3	GLOBAL WATER	0.120	23.03.2020	30.08.2021	0.712
4	WIND	0.103	07.06.2006	14.11.2007	0.736

Source: Own study.

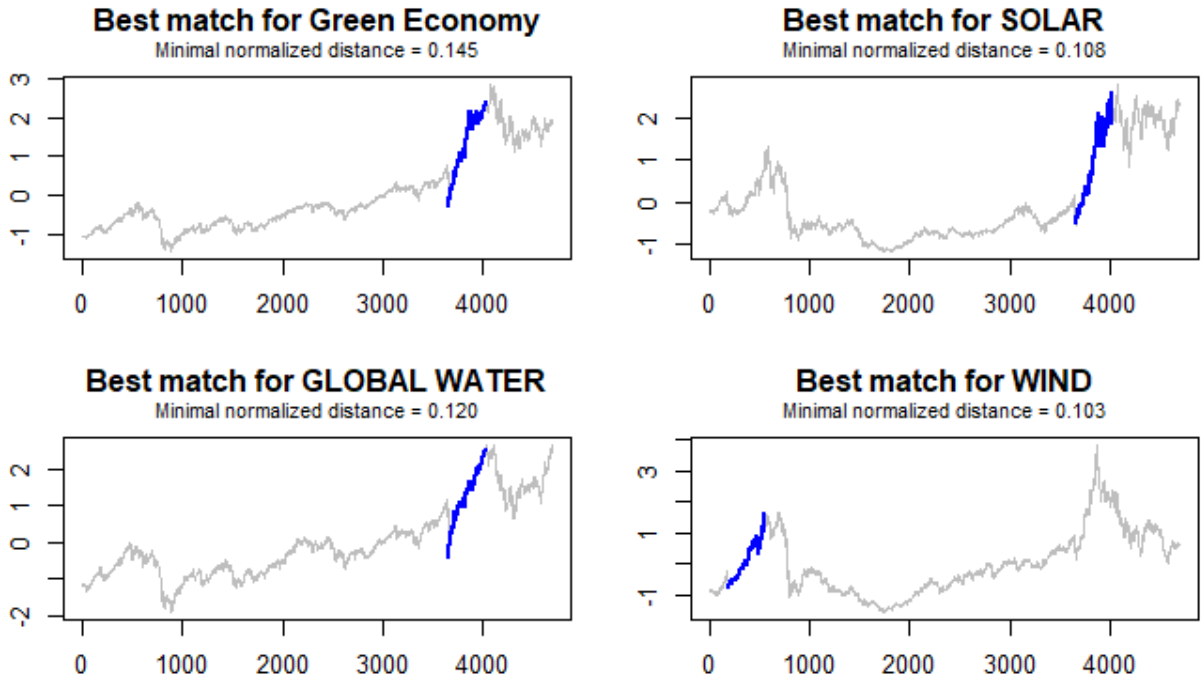
Based on the data from Table 2, it can be concluded that for three out of the four examined series, the best fit to the pattern was achieved during the exact same periods. This result is surprising given the length of the analysed time series. For the Green Economy, SOLAR and GLOBAL WATER indices, the period with the optimal fit began on March 23, 2020 and ended on August 30, 2021. For the WIND index, the optimal period was from June 7, 2006 to November 14, 2007. However, it should be noted that during the previously mentioned period for the other three indices, the WIND index also achieved a moderate fit value of around 0.30.

Such low fit values in the period from March 23, 2020 to August 30, 2021 should be associated with the World Health Organization's declaration of COVID-19 as a pandemic and investors seeking new investment opportunities while traditional capital markets worldwide were experiencing record high

declines, as demonstrated in the works of Al-Awadhi et al. (2020), Fang et al. (2023), Harjoto et al. (2021) and Jin et al. (2022). At that time, companies in the green economy sector, as well as in the modern technology sector, cryptocurrencies and gold, traditionally considered a safe haven during crises, emerged as alternative investment options for many investors (Basse et al., 2023; Cheema et al., 2022; Chemkha et al., 2021; Ji et al., 2020; Zeng et al., 2023).

Figure 2 highlights the moment of the best pattern fit to the quotations for the main indices of the analysed market.

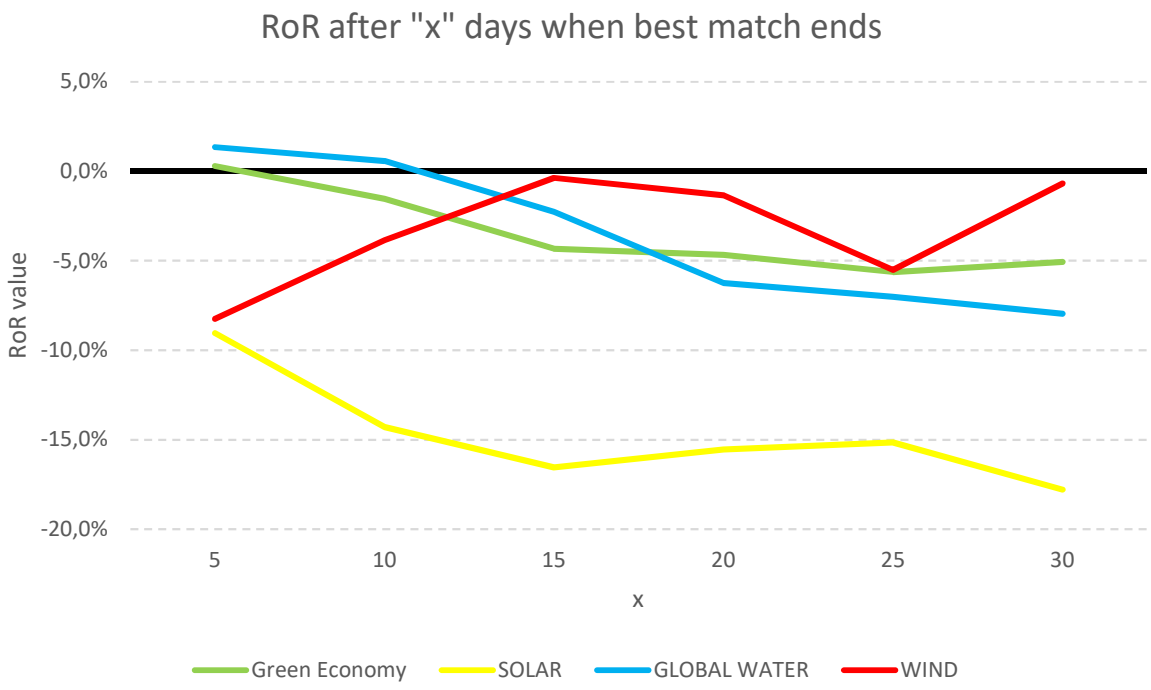
Figure 2 Indication of the optimal fit of the quotations of the main market indices to the pattern



Source: Own study.

Based on the data from Figure 2, it can be concluded that the COVID-19 pandemic caused a price bubble phenomenon in the green economy markets, characterised by an approximately one-and-a-half-year phase of euphoria, which was followed by significant price declines. These declines were observed for each of the examined indices, although their magnitude should be considered individually depending on the number of days after the end of the optimal fit phase. For this purpose, Figure 3 was prepared. It presents the return rate value after the end of the optimal fit phase in the following weeks.

Figure 3 Return rate value achieved in the following weeks after the end of the euphoria phase



Source: Own study.

Based on the data presented in Figure 3, it can be concluded that the indicated end of the optimal euphoria phase fit resulted in price declines ranging from -0.37% to -17.79% in the following weeks. Additionally, three positive values were noted for the GLOBAL WATER index after 5 and 10 days, amounting to 1.35% and 0.57% respectively, and for the Green Economy index after 5 days, amounting to 0.29%. For these three cases, despite the end of the euphoria phase being indicated, small increases in these indices were still observed. In other cases, it can be stated that the DTW algorithm correctly indicated the end of the euphoria phase, achieving an average decline of over 6%, with the largest drops recorded for the SOLAR index. These results demonstrate that the DTW procedure is useful for determining the end of the euphoria phase, and by using it, one can achieve above-average returns through short selling within 6 weeks, as confirmed by the data in Figure 3.

b. Results by geographic region

In the next step, calculations were made for indices that consider the division into geographic regions. In this section of the work, two types of indices were examined. The first type is indices from the "Green Economy" (GE) family, and the second type is indices belonging to the Clean Energy Focused (CE) group. These two types of indices were analysed by geographic regions, including Asia, Europe, the United States of America, and companies that are not part of the United States of America market. The results of the best and the most recent fit for these indices are presented in Table 3.

Table 3 Best and last match for geographic indices

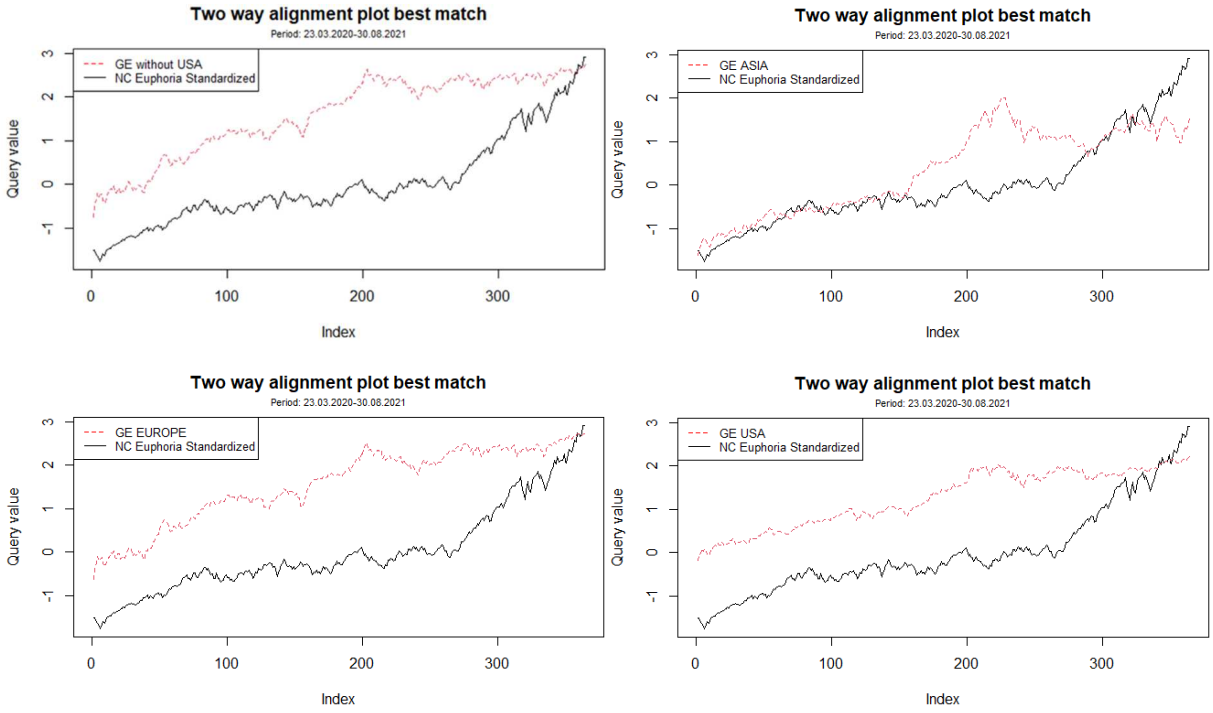
		Best match			Last match
No.	Index name	Minimal normalised distance	Start date	End date	Normalised distance
1	GE ASIA	0.084	23.03.2020	30.08.2021	0.769
2	GE EUROPE	0.097	23.03.2020	30.08.2021	0.561
3	GE USA	0.172	23.03.2020	30.08.2021	0.867
4	GE without USA	0.087	23.03.2020	30.08.2021	0.639
5	CE ASIA	0.107	30.08.2019	09.02.2021	0.548
6	CE EUROPE	0.071	07.06.2006	14.11.2007	0.607
7	CE USA	0.240	23.03.2020	30.08.2021	0.929
8	CE without USA	0.076	01.06.2006	08.11.2007	0.695

Source: Own study.

Based on the data from Table 3, it can be observed that for the GE family indices, all the best fits come from the same period, namely after the declaration of COVID-19 as a pandemic. The value of the minimal fit is below 0.10 for the indices from Asia, Europe and companies not within the USA . For the USA index, the value of the minimal fit is 0.172, which is nearly twice as high as for the other examined indices. In the case of the CE group indices, only the index from the USA region recorded the same period for the optimal fit. For the Asia index, the beginning of the best fit was established on August 30, 2019, while for the indices from Europe and companies not within the USA, the best fit to the euphoria phase was demonstrated from June 2006. This last optimal fit period is associated with the Great Financial Crisis, which was preceded by significant market increases in 2005, 2006 and partially in 2007. The optimal fit results for the GE indices indicate that, regardless of the region, investors during the crisis moved their funds to companies associated with the broadly understood Green Economy sector. This was not unequivocally confirmed for the Clean Energy indices. Additionally, it was not demonstrated that these indices are currently in a euphoria phase similar to the one considered as the benchmark. The latest fit results for all indices in this group range from 0.548 to 0.929, indicating significant discrepancies between the adopted benchmark and the latest quotations of the examined indices. The scale of capital transfer to the green economy market after the COVID-19 pandemic is evidenced by the term "painted green," which refers to the pretension of actions aimed at presenting a company as belonging to the green economy sector (Demidov, 2022). Companies were engaged in such actions due to the ease of obtaining capital for firms operating in the green economy sector, which was supported by international regulations such as the United Nations 17 Sustainable Development Goals and the Paris Agreement (Gunay et al., 2022).

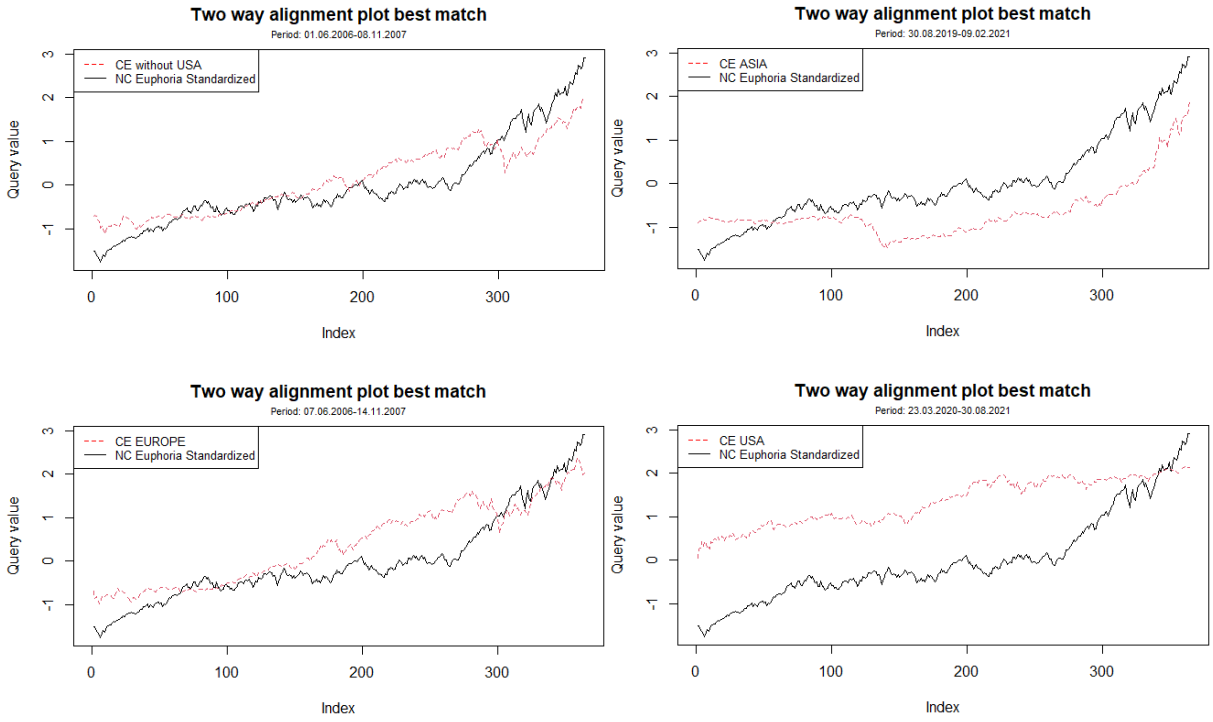
The detailed course of the examined data series with the adopted pattern is presented in Figures 4 and 5.

Figure 4 Course of the Green Economy family indices by geographic region against the benchmark



Source: Own study.

Figure 5: Course of the Clean Energy family indices by geographic region against the benchmark



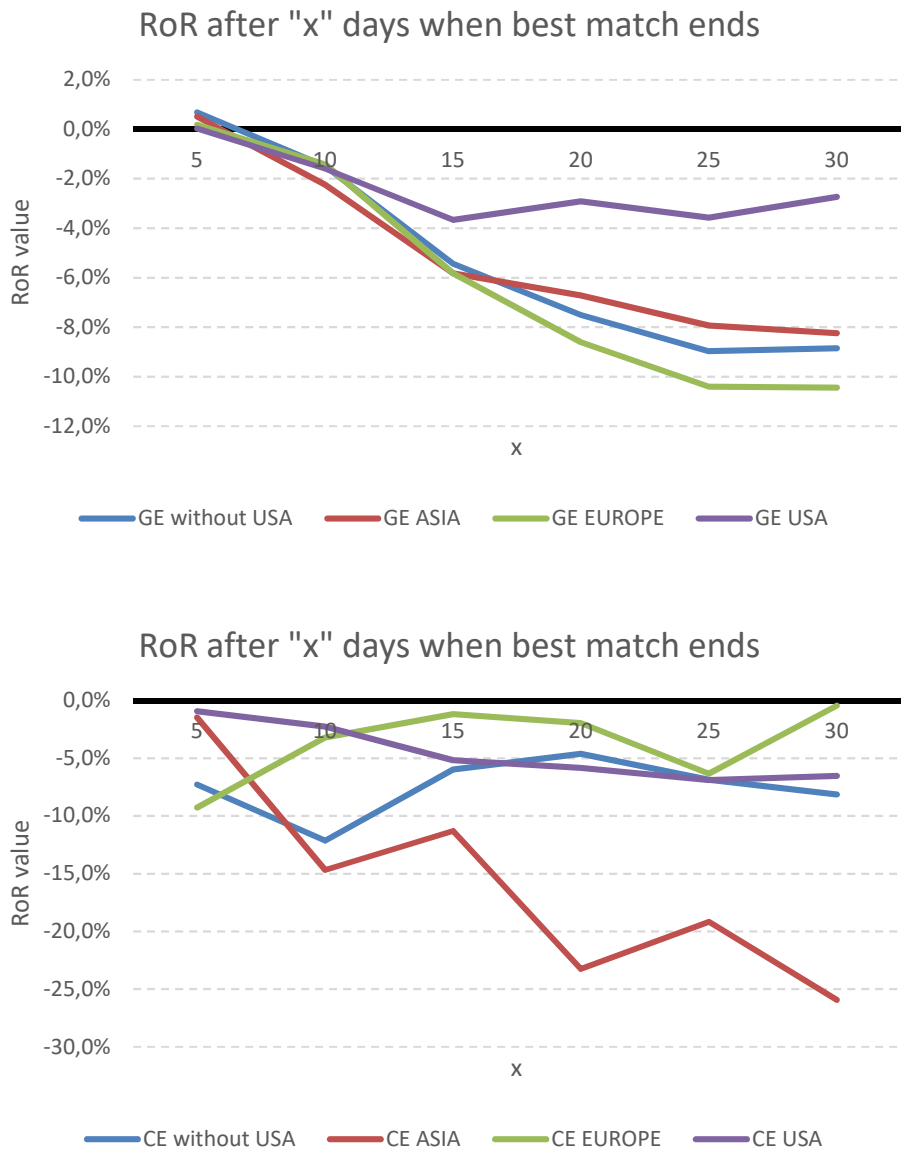
Source: Own study.

Figure 4 shows the course of the examined Green Economy family indices against the benchmark. Both data series are standardised and overlaid to illustrate the optimal fit and to show what influenced the obtained value of the minimal distance. The lowest value in the geographic cross-sectional study shown in Figure 4 was achieved for the GE ASIA index. As seen in the figure, this index exhibits an almost identical course to the benchmark in the initial phase. It is only around the 150th day of quotations that the index for Asia reaches higher levels, peaking on the 228th day before its quotations stabilised. The highest value of the minimal distance, indicating the worst fit in this group, was obtained for the GE USA index. For this index, a systematic increase in quotations was observed throughout the period, but without the distinct surge in quotations characteristic of the euphoria phase.

Similarly, the CE USA index also had the highest value of minimal distance among the indices from the "Clean Energy" family, as shown in Figure 5. In contrast, the fit for the other three indices in this group was quite different, with minimal distance values more than twice as low. It is important to note that a weakness of the DTW procedure is its potential inability to detect that a given index is characterised by a stable upward trend, which may not necessarily end in significant declines.

The values of the obtained returns after 5, 10 and subsequent weeks of quotations are presented in Figure 6.

Figure 6 Return rate value achieved in the following weeks after the end of the euphoria phase



Source: Own study.

As shown by the data in Figure 6, all the indices in this group experienced average negative returns regardless of the time after the end of the euphoria phase. On average, one week after the end of the euphoria phase, the return rate was -2.2%, reaching the highest average level of -8.9% six weeks after the determined end of the euphoria phase. The largest declines were recorded for the GE EUROPE index among the GE family and the CE ASIA index in the second group. After thirty days, these declines were -10.4% and -25.9%, respectively. In both cases, the value of the minimal distance was at a low level, and the obtained results indicate that the DTW methodology can be used to achieve above-average profits. This is effective when the value of the minimal fit does not exceed 0.15. Additionally, after analysing the course of the examined index and excluding any potential steady but moderate

upward trend without a distinct surge in quotations, short selling can be applied to achieve above-average returns.

c. Results for sectors of the green economy

Table 4 presents the results for the optimal and most recent fit for indices across sectors. The sectors are arranged according to the value of the minimal distance.

Table 4 Best and last match for sectoral indices

		Best match			Last match
No.	Index name	Minimal normalised distance	Start date	End date	Normalised distance
1	ADVANCED MATERIALS	0.066	23.03.2020	30.08.2021	0.712
2	GREEN BUILDING	0.069	29.05.2020	04.11.2021	0.341
3	FUEL CELL	0.078	01.08.2019	08.01.2021	0.596
4	ENERGY STORAGE	0.089	03.09.2019	10.02.2021	1.179
5	BIO/CLEAN FUELS	0.095	18.03.2020	25.08.2021	0.410
6	SMART GRID	0.098	23.03.2020	30.08.2021	0.740
7	ENERGY MANAGEMENT	0.099	23.03.2020	30.08.2021	0.875
8	RENEWABLE ENERGY	0.113	18.07.2006	26.12.2007	0.912
9	GEOTHERMAL	0.113	08.08.2018	17.01.2020	0.880
10	NATURAL RESOURCES	0.117	23.03.2020	30.08.2021	1.194
11	HEALTHY LIVING	0.119	18.03.2020	25.08.2021	0.525
12	TRANSPORTATION	0.141	15.08.2019	25.01.2021	0.684
13	LIGHTING	0.144	16.03.2020	23.08.2021	0.454
14	DEVELOPER/OPERATOR	0.164	23.05.2006	31.10.2007	0.945
15	RECYCLING	0.166	23.03.2020	30.08.2021	0.922
16	CLEAN ENERGY	0.187	23.03.2020	30.08.2021	0.847
17	ENRGY EFFICIENCY	0.195	23.03.2020	30.08.2021	0.795
18	GREEN IT	0.211	30.11.2016	11.05.2018	0.718
19	POLLUTION MITIGATION	0.219	18.03.2020	25.08.2021	0.650

Source: Own study.

Based on the data from Table 4, it can be concluded that, similar to the previous indices, most periods with an optimal fit begin in March 2020. This is the case for 11 out of the 19 analysed indices. This confirms the previously indicated trend of significant investor interest in the green economy market due to the COVID-19 pandemic, as highlighted by Ferreira & Morais (2022) and Zeng et al. (2023). For 13 out of the 19 examined indices, the value for the optimal fit did not exceed 0.150 for the normalised distance, indicating a very good fit of these indices to the pattern. For the remaining six indices, this value ranged from 0.164 to 0.219. Additionally, the results from Table 4 indicate that the current sectors cannot be said to be in a phase similar to the euphoria phase of the dot-com bubble period.

The values of the latest fits average 0.757, and for two indices, NATURAL RESOURCES and ENERGY STORAGE, the value exceeds 1.

The next table presents the return rates calculated from the end of the period representing the best fit to the euphoria phase. Table 5 contains the return rates calculated for subsequent weeks from the end of the optimal fit period.

Table 5 RoR after "x" days when the best match ends

	Days after best match ends:					
Index name	5	10	15	20	25	30
ADVANCED MATERIALS	-0.1%	-0.7%	-4.6%	-6.2%	-8.7%	-9.8%
GREEN BUILDING	-0.1%	-0.1%	-3.2%	-4.5%	-2.2%	-4.5%
FUEL CELL	9.3%	22.3%	20.8%	31.1%	17.3%	-6.5%
ENERGY STORAGE	-3.6%	-2.0%	-7.3%	0.6%	0.3%	-6.0%
BIO/CLEAN FUELS	-0.4%	-2.9%	-1.2%	-1.3%	-1.6%	0.5%
SMART GRID	-0.8%	-1.4%	-6.0%	-8.0%	-9.2%	-8.8%
ENERGY MANAGEMENT	-0.4%	-2.3%	-6.1%	-7.5%	-8.5%	-10.4%
RENEWABLE ENERGY	0.2%	-9.8%	-20.8%	-24.3%	-22.0%	-27.4%
GEOTHERMAL	2.3%	1.8%	6.9%	8.8%	1.0%	-10.4%
NATURAL RESOURCES	-2.1%	-6.7%	-11.1%	-7.3%	-11.0%	-12.8%
HEALTHY LIVING	-0.7%	-2.6%	-3.2%	-2.2%	-5.8%	-6.0%
TRANSPORTATION	-4.7%	-1.3%	-5.9%	-14.6%	-15.4%	-16.7%
LIGHTING	1.4%	-0.6%	-2.6%	-6.8%	-8.2%	-10.4%
DEVELOPER/OPERATOR	-1.5%	-2.9%	-5.8%	-4.2%	-1.9%	-3.4%
RECYCLING	-1.7%	-4.1%	-7.1%	-6.4%	-7.4%	-6.3%
CLEAN ENERGY	-0.4%	-1.8%	-5.6%	-7.0%	-8.7%	-8.2%
ENRGY EFFICIENCY	-1.0%	-2.5%	-6.1%	-6.5%	-7.9%	-9.0%
GREEN IT	-4.7%	-5.3%	-3.9%	-3.0%	-1.3%	-5.6%
POLLUTION MITIGATION	2.2%	0.5%	-1.1%	-2.7%	-9.2%	-9.5%

Source: Own study.

The data in Table 5 confirm the high effectiveness of using the DTW methodology to achieve above-average profits and determine the end of the euphoria phase. For 18 out of the 19 examined indices, negative returns were recorded 30 days after the optimal fit period ended. The only exception is the BIO/CLEAN FUELS index, which had a return rate of 0.5% after 30 days. It is also worth noting the return rates for the FUEL CELL and GEOTHERMAL indices. These two indices recorded significant positive returns up to 25 days after the optimal fit period ended. This indicates that, despite the low value of the optimal distance, the end of the euphoria phase was determined too early for these indices, as the declines only appeared in the 6th week. However, excluding these two indices, the average return rate for the remaining 17 indices was -1.1% after 5 days from the end of the euphoria phase, -2.7% after 10 days, -6.0% after 15 days, -6.6% after 20 days, and -7.6% and -9.1% after 25 and 30 days, respectively.

This demonstrates the high effectiveness of using the DTW method to determine the end of the euphoria phase for the examined indices.

5. Conclusion

In this article, dynamic time warping analysis was used to verify whether the market known as green finance is currently in a phase that can be described as a phase of euphoria. This is a characteristic stage of price bubble formation that occurs before a market crash. The study used the Nasdaq Composite index quotations from the dot-com bubble period as the benchmark pattern. The conclusions drawn from the analyses, which provide answers to the research questions defined in the introduction, are presented below.

Firstly, the green economy market is not currently in a phase of euphoria. This is evidenced by the values of the calculated distances obtained using the DTW method. This statement is true both for the main indices studied and the indices representing geographic and sectoral cross-sections. The obtained study results indicate that the current quotations of the examined indices cannot be compared to the euphoria phase observed during the dot-com bubble. However, two indices, GREEN BUILDING and BIO/CLEAN FUELS, should be monitored in this context, as their quotations achieved the lowest values for the latest fit, at 0.341 and 0.410, respectively. This suggests that in the near future, both indices may experience high positive returns.

Secondly, similar to previous studies (Ferreira & Morais, 2022; Zeng et al., 2023), it was confirmed that the lowest distance values were obtained for quotations in the year of the outbreak of the COVID-19 pandemic. This indicates that during that time, the quotations of the examined indices entered a phase of euphoria. The optimal fit value was obtained in 2020 for 20 out of the 31 indices studied. Importantly, the optimal fit values for all the indices were below 0.25, indicating a very good fit to the adopted benchmark.

Thirdly, the study demonstrated the usefulness of the DTW (dynamic time warping) method for identifying the euphoria phase for any index. This method can be practically applied to real-world data analysis. The advantage of this research approach is its ability to detect the euphoria phase and indicate its end before significant market corrections occur following the peak growth periods. This makes the method more suitable for practical applications than, for example, the GSADF test (Phillips et al., 2015), which can also be used to detect ongoing price bubbles.

The above conclusions are undoubtedly valuable insights for investors, market analysts and policymakers. They can be used to design investment strategies based on short selling after the end of

the euphoria phase. The results presented in this article indicate the high effectiveness of such strategies within 30 days of identifying the end of the euphoria phase.

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