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Explosiveness in the renewable energy equity sector: International evidence

Juan Ariza, Román Ferrer *

Department of Financial and Actuarial Economics, University of Valencia, Spain

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This paper investigates episodes of explosiveness in the renewable energy equity sectors of the three major economic regions, namely the U.S., China, and Europe, as well as the degree of connectedness between these regional renewable energy sectors and their respective broader stock markets. To this end, the novel methodology developed by Phillips and Shi (2019) is employed in conjunction with the robust bootstrap procedure of Phillips and Shi (2020). Furthermore, the connectedness framework of Diebold and Yilmaz (2012, 2014) is used to assess return connectedness. The empirical results reveal significant episodes of explosiveness within the renewable energy sectors across the three regions. The principal period of explosivity began in late 2020 within U.S. and European renewable energy stocks, following the initial COVID-19 pandemic wave, and subsequently spread to Chinese renewable energy stocks. However, there is limited co-explosivity between the renewable energy sectors and broader stock markets, indicating that the explosive dynamics in renewable energy equities do not pose a systemic threat for the general stock markets. Additionally, the study reveals a decrease in connectedness between the regional renewable energy sectors and their broader market counterparts during the recent explosive periods, likely reflecting the decoupling of renewable energy stocks from general market trends during the latter stages of the renewable energy bubble.

1. Introduction

In recent years, the renewable energy sector has experienced extraordinary expansion, driven by a confluence of factors. These include greater environmental consciousness, strong governmental support through incentives and regulations, significant breakthroughs in clean technology that have dramatically reduced production costs, and evolving consumer preferences for sustainable energy solutions. This growth has been especially pronounced in key regions such as the United States, China, and Europe. Despite this impressive progress, the sector still faces substantial challenges, such as infrastructure bottlenecks, complex regulatory frameworks, and high upfront investment costs, which are partially impeding widespread adoption of renewable technologies. Nevertheless, the future outlook for the renewable energy sector remains highly optimistic. Market research firm *Straits Research* forecasts that the global renewable energy market, valued at USD 1,085 billion in 2023, will reach USD 2,450 billion by 2032, representing a robust compound annual growth rate (CAGR) of 9.47 %. This projected growth is underpinned by several driving forces, including escalating global energy demand, the increasing incorporation of renewables into power generation, and government policies aimed at reducing

* Corresponding author at: Dpto. de Economía Financiera y Actuarial, Facultad de Economía. Universidad de Valencia, Avda. Tarongers, s/n, 46022 Valencia, Spain.

E-mail address: roman.ferrer@uv.es (R. Ferrer).

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dependence on traditional fossil fuels and promoting sustainability. This unprecedented expansion of the renewable energy sector has also translated into the stock market, leading to a surge in renewable energy stocks worldwide. Once considered niche investments, these stocks have now evolved into a mainstream choice for investors. Some market analysts have drawn parallels between the recent boom in renewable energy equities and the technology stock bubble of the late 1990 s, which culminated in the dot-com crash. Similarities are noted in the rapid escalation of stock prices and the emergence of an industry with far-reaching structural effects on the global economy (Olsen, 2021; Lehnert, 2023).

The enthusiasm surrounding renewable energy stocks has raised concerns about the potential formation of a speculative bubble over the last few years (Aramonte and Zabai, 2021; Jourde and Stalla-Bourdillon, 2021, 2024). Private investors, attracted by the promise of outstanding short-term returns, have had powerful incentives to pour capital in what some are calling a "green bubble". This risk has been further exacerbated by both political and social pressures. On the one hand, governments around the world have allocated huge amounts of public funds to support clean energy investments, with the aim of accelerating progress towards their net-zero emissions goals. This dynamics creates an environment where private actors might expect some form of government intervention or bailouts should the sector faces difficulties, potentially leading to excessive risk-taking and overvaluation of renewable energy stocks relative to their fundamentals. On the other hand, social pressure, fueled by the increased demand for environmentally friendly investments, can encourage herd behavior, further inflating the sector's asset prices.

Given the pivotal role of the renewable energy sector in financing the global transition to a low-carbon world, it is crucial for investors and policymakers to closely monitor potential speculative excesses in this sector. A boom-and-bust cycle could not only inflict financial and social costs but also derail the energy transition process towards a cleaner economy. However, it is also important to recognize that explosive episodes in clean energy stock prices are not inherently harmful to the economy and society. According to the social bubble hypothesis proposed by Gisler et al. (2011), clean-tech bubbles can act as significant catalysts for technological innovation and the large-scale adoption of renewable energy technologies, ultimately enhancing productivity and economic growth (Giorgis et al., 2022).

In this context, the primary objective of this research is to investigate the presence of explosive behavior within the renewable energy equity sector at the international level over recent years, employing the method introduced by Phillips and Shi (2019). This framework builds upon the well-established bubble identification procedure pioneered by Phillips et al. (2015a,b) and offers several advantages over alternative methods. First, a key feature of the Phillips and Shi (2019) technique is its ability to simulate a variety of realistic price behavior scenarios, enabling the detection of both market expansions and crashes. Second, it allows for precise estimation of the origination and collapse dates of explosive episodes. Third, it mitigates the delay bias in detecting the emergence of explosiveness typically associated with the method of Phillips et al. (2015a,b). Furthermore, to address potential distortions caused by heteroskedasticity and multiplicity issues in recursive testing, this study also utilizes the composite bootstrap scheme proposed by Phillips and Shi (2020). Additionally, this work examines the interdependence between regional renewable energy equity sectors and their broader stock markets through the connectedness framework developed by Diebold and Yilmaz (2012, 2014). This analytical tool offers valuable insights into the transmission of shocks across renewable energy stock returns and general stock returns. By uncovering potential vulnerabilities and contagion effects within and between regional renewable energy sectors and broader stock markets, this framework provides a powerful mechanism for assessing systemic risks associated with the rapid growth of renewable energy stocks.

This research contributes to the existing literature on stock market explosiveness across various dimensions. First, to the best of our knowledge, no previous work has specifically examined explosive behavior in renewable energy equities across the three major economic regions (the U.S., China, and Europe). While earlier studies have focused on identifying bubbles in renewable energy stock prices within individual regions such as the U.S. or Europe, this research adopts a more holistic perspective that encompasses all three regions. Second, from a methodological standpoint, it employs the novel bubble detection framework of Phillips and Shi (2019), alongside the heteroskedasticity- and multiplicity-robust bootstrap procedure designed by Phillips and Shi (2020). Third, it covers an updated sample period that includes two critical recent events, namely the COVID-19 pandemic and the ongoing Russia-Ukraine war. Fourth, it explores potential co-explosivity between renewable energy equities and general stock markets in these regions. Lastly, it investigates the transmission of shocks between renewable energy equity sectors and the broader stock markets. By identifying regional disparities in explosive behavior and assessing the degree of interdependence between regional renewable energy equity sectors and general stock markets, this study offers a comprehensive framework for understanding the evolving risks and opportunities within the global renewable energy sector, informing both investors and policymakers.

Our empirical findings show episodes of explosiveness in the renewable energy equity sectors across these regions, particularly emerging from late 2020 in the wake of the initial surge of the COVID-19 pandemic. The renewable energy sector's elevated propensity for explosive dynamics, compared to general stock markets, can be attributed to several factors, including increased focus on sustainability and environmental concerns following the onset of the pandemic, historically low interest rates, supportive governmental policies promoting renewable energy, and declining costs of clean technologies. Importantly, there is limited evidence of co-explosivity between regional renewable energy equity sectors and broader stock markets, suggesting that exuberance in in renewable energy stock prices does not pose a significant systemic threat to general stock markets. The connectedness analysis reveals a significant degree of return spillovers between renewable energy equity sectors and general stock markets throughout the sample period, peaking in March 2020 at the height of the COVID-19 crisis. The U.S. general stock market emerges as the primary transmitter of spillovers, with the U.S. renewable energy sector and the European general stock market playing a secondary role. Conversely, the European and Chinese renewable energy sectors, along with the Chinese general stock market, are identified as receivers of spillovers. Interestingly, return spillovers diminish during the post-pandemic period of explosive growth in the global renewable energy sector, possibly reflecting the decoupling of renewable energy equities from general market behavior during the latter stages of this green bubble.

The rest of the paper is organized as follows. Section 2 discusses the concept of financial bubble and its potential consequences.

Section 3 reviews the most pertinent literature on stock market explosiveness, particular focusing on renewable energy stocks and their interconnectedness with other assets. Section 4 outlines the methodological framework employed, while Section 5 describes the dataset used in this study. Section 6 presents and analyzes the empirical findings. Finally, Section 7 offers some concluding remarks.

2. Understanding financial bubbles and their consequences

The phenomenon of asset price bubbles is not something new, but history is replete with instances ranging from the Dutch Tulip mania of 1636–1637, which is widely regarded as the first asset bubble of the modern era, to more recent episodes such as the dot-com bubble of the 1990 s and the U.S. housing bubble of 2003–2006.[1] Prominent historical bubbles also include the Mississippi bubble in France in 1719–1720, the South Sea Bubble in the UK in 1720, the Australian Land Boom of 1886–1893, and the Japanese bubble economy of 1985–1992. The term "financial bubble" has been defined in several ways in academic literature. One of the most commonly accepted definitions posits that a bubble occurs when the price of an asset significantly and persistently deviates from its fundamental or intrinsic value. A simpler yet widely cited definition comes from Charles Kindleberger, the MIT economic historian and bubble scholar, who described a bubble as an "upward price movement over an extended period that then implodes" (Aliber and Kindleberger, 2005). Essentially, a bubble is characterized by a substantial and prolonged increase in an asset's price, followed by a sharp, often sudden, collapse. Quinn and Turner (2020) develop a structured framework for understanding the necessary conditions that typically give rise to asset price bubbles. They identify three critical elements, namely marketability, speculation, and money and credit, which are collectively termed the "bubble triangle". Marketability refers to how easily an asset can be traded in the market, reflecting its liquidity. Speculation involves investors buying or selling assets based on expectations of future price movements, often driven by market sentiment rather a solid underlying rationale. Lastly, money and credit pertain to the availability of financial resources, which are also crucial for inflating asset prices. Without ample liquidity, prices are unlikely to experience significant upward pressure. In periods of low interest rates, abundant liquidity encourages leverage, further fueling speculative behavior. n addition, when traditionally safer assets like fixed-income securities offer low returns, investors often shift toward riskier investments in search of higher yields, thus exacerbating bubble dynamics. When these three elements converge, the stage is set for a bubble, and it only takes a spark for it to burst.

The bursting of financial bubbles is typically accompanied by a cascade of adverse economic effects with far-reaching consequences. First, bubbles often lead to a misallocation of capital, as resources are diverted into speculative assets instead of being directed toward productive investments, thereby distorting economic priorities and hindering long-term economic growth. Second, bubbles foster short-termism and irrational trading behavior, contributing to heightened market volatility. As speculative fervor intensifies, market participants are driven by momentum and herd behavior rather than fundamental analysis, which undermines confidence in long-term investment strategies and increases systemic risk. Lastly, when bubbles inevitably burst, the resulting financial losses suffered by investors, companies, and financial institutions can trigger systemic shockwaves, potentially culminating in widespread economic downturns or even precipitating full-blown financial crises.

Stock markets have historically been fertile ground for bubble formation, as they offer liquidity and accessibility that fuel speculative behavior. Investors, often lured by the prospect of rapid and easy gains in booming sectors or companies, tend to disregard fundamental valuations and instead chase market trends. The ease of entry and exit in stock markets exacerbates this tendency, fostering irrational behavior as investors collectively follow sentiment-driven narratives. This cycle of speculation is a common phenomenon in the stock market, typically resulting in strong bullish trends that eventually lead to severe market corrections or collapses once the underlying bubble bursts.

Despite their generally negative connotations, some bubbles can yield beneficial effects on the sectors involved and even the broader economy through various mechanisms. Firstly, bubbles have the potential to attract substantial capital flows to a particular sector, driving investment in new technologies and accelerating innovation, which can fuel long-term economic growth. Secondly, companies benefiting from bubble-induced capital inflows may diversify their resources into other sectors, creating cross-sectoral synergies and opening up new economic opportunities. Thirdly, bubbles can also unlock funding for projects that might otherwise struggle to obtain financing. In this regard, Lehnert (2023) contends that the recent surge in green stocks can be viewed as a beneficial bubble that has significantly expedited the growth of renewable energy companies. By easing access to capital, this bubble has accelerated and amplified investments in sustainable technologies, thereby contributing to the global transition away from fossil fuels and reinforcing efforts to combat climate change.

3. Literature review

The serious financial and economic repercussions of the bursting of stock price bubbles have spurred extensive research focused on the detection of explosive behavior in global stock markets. Most of these studies have centered on market-wide indices of major economies, such as the U.S. (Homm and Breitung, 2012; Phillips et al., 2015a; Basse et al., 2021), Europe (Caraiani and Călin, 2020; Hudepohl et al., 2021), and China (Jiang et al., 2010; Shu and Zhu, 2020; Wang et al., 2021). These works have successfully identified

[1] The Dutch Tulip mania stands as one of the most iconic asset bubbles in financial history. By late 1636, tulip bulbs, particularly rare varieties, became a powerful symbol of social status. Prices for certain bulbs soaring to unprecedented levels, with some valuations higher than that of a luxurious townhouse in Amsterdam. However, this speculative frenzy was short-lived. By February 1637, the marke collapsed, leaving tulip bulbs virtually worthless.

several instances of market explosiveness, including the dot-com bubble in 2000, the 2007–2008 global financial crisis, and the 2015 Chinese stock market crash. By contrast, far less attention has been directed towards speculative bubbles at the sectoral level, with a few notable exceptions exploring the U.S. Nasdaq technology index (Monschang and Wilfling, 2021; Demmler and Fernández, 2024) and a wide range of sectors within the Chinese stock market (Yang and Ferrer, 2023).

The spectacular expansion of the renewable energy sector in recent years has fueled growing interest in the formation of bubbles in renewable energy equities. Pioneering work in this area by Bohl et al. (2013) applied the Supremum Augmented Dickey-Fuller (SADF) test of Phillips et al. (2011) and the Markov regime-switching ADF test of Funke et al. (1994) to investigate explosive price behavior in German renewable energy stocks. They detected speculative bubbles between 2004 and 2007, driven by positive market sentiment towards the German renewable energy sector in the lead-up to the 2007–2009 global financial crisis. In the same vein, Bohl et al. (2015) analyzed bubble-like behavior in five European, U.S., and global alternative energy sectors during the mid-2000 s employing the PSY approach. They provided strong evidence of explosive dynamics in European and global clean energy indices from 2005 to 2007, followed by a sharp collapse in 2009. This substantial revaluation of alternative energy stock prices likely reflected intensified competition and shrinking margins within the sector. However, no signs of explosiveness were found in U.S. renewable energy stocks during this period. Wang et al. (2020), also using the PSY method, identified bubble behavior within the Chinese wind, solar, and hydropower industries. Olsen (2021) conducted a similar analysis for the Oslo Børs Benchmark Index (OSEBX) and 21 renewable energy stocks listed on the Oslo Stock Exchange or the Euronext Growth market. Her findings indicated that, although the OSEBX did not exhibit bubble characteristics, 13 individual renewable energy stocks experienced exuberant growth between late 2020 and early 2021.

Similarly, Giorgis et al. (2022) applied the Log-Periodic Power Law Singularity (LPPLS) methodology to the global renewable energy equity sector, as represented by the RENIXX index, uncovering bubble behavior in clean technology sub-sectors, such as solar, biofuels, batteries, and other renewables, between 2004 and 2008. Ghosh et al. (2022) utilized the same model to identify multiple asset bubbles in U.S. and European renewable energy-focused assets during the pandemic era (2019–2021). These authors noted that, contrary to conventional wisdom, these green bubbles might not be necessarily detrimental, as they stimulate economic activity and infrastructure development, promoting broader growth. Lehnert (2023), using the PSY procedure, identified an episode of explosive growth in U.S. green energy stocks, particularly in the NASDAQ Clean Edge Green Energy index, beginning in July 2020. This exuberance extended to the general U.S. stock market, which Lehnert interprets as a beneficial bubble, accelerating investment in renewable energy and expediting the transition away from fossil fuels. More recently, Foglia and Miglietta (2024) have examined explosive dynamics in Environmental, Social, and Governance (ESG)-related investments, applying the LPPLS approach to MSCI ESG Leaders indices, which are weighted average stock indices comprising firms with high ESG ratings. Their results show multiple bubble periods between 2010 and 2013 across the U.S., Europe, and emerging countries, with varying durations. In a comprehensive analysis, Potrykus et al. (2024) have analyzed price bubbles and co-bubbles in the new green economy market. Their findings show clear evidence of explosive behavior in the green market, particularly in solar and wind sectors, with peaks during the COVID-19 pandemic and the Russia-Ukraine war.

This study also aligns with the extensive literature on connectedness and contagion effects across international stock markets, especially during periods of financial distress, such as the Mexican, East Asian, and Russian crises of the 1990 s, the 2007–2008 global financial crisis or the COVID-19 pandemic. The connectedness among equity markets has been significantly reinforced by the processes of financial liberalization and economic globalization, which have amplified cross-border capital flows and tightened economic and financial interdependencies between nations. However, as pointed out by Forbes and Rigobon (2002), contagion refers to a substantial increase in market connectedness during times of crisis. Contagion occurs when financial shocks spread from one market to others, beyond what would be anticipated based on existing economic and financial linkages under normal conditions. A large body of empirical research has presented evidence of international equity market contagion during various financial crises (King and Wadhwani, 1990; Calvo and Reinhart, 1996; Dungey et al., 2007; Lien et al., 2018; Wang et al., 2023). In another interesting contribution, Hernández and Valdés (2001) illustrate how, when stock market returns are used as crisis indicators, different contagion channels dominate depending on the specific event. During the Thai and Brazilian crises of the 1990 s, trade links and neighborhood effects were critical drivers of contagion among stock returns of 17 emerging economies. By contrast, in the case of the Russian crisis, financial competition emerged as the only relevant channel of contagion. More recently, Yu et al. (2024) have investigated risk contagion effects among 50 national stock markets employing a comprehensive methodological framework that integrates the ΔCoVaR model, time-varying spillover methods, and complex network analysis. Their results show pronounced contagion effects among global stock markets, particularly for developed countries, which intensify during extreme risk events. Factors such as international trade, cross-border capital flows, financial market volatility, investor sentiment, and U.S. monetary policy significantly influence the dynamics of risk contagion.

Most directly related to the present research, a number of studies have explored connectedness between renewable energy stocks and other financial assets and commodities. For example, Ferrer et al. (2018) examined connectedness among U.S. renewable energy stocks, crude oil prices, and several key financial variables over time and across frequencies simultaneously using the methodology of Baruník and Křehlík (2018). Their results reveal that most of connectedness occurs in the very short-term (up to five days). Interestingly, crude oil prices do not exert a significant influence on the stock performance of renewable energy companies, suggesting that the alternative energy industry is increasingly decoupling from the traditional energy market. Likewise, Arif et al. (2021) analyzed the time–frequency connectedness between green financial markets and conventional financial and energy markets using the connectedness frameworks of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). They found weak spillovers between conventional and green financial markets. In fact, there are only one-way spillovers from ordinary bonds to green bonds. Furthermore, increased connectedness was observed during periods of crisis, such as the COVID-19 pandemic, suggesting that financial stability may play a significant role in determining the smooth transition to green investments. Along the same lines, Chai et al. (2022) employed a time-varying parameter vector autoregression (TVP-VAR) model to assess the dynamic nonlinear connectedness between green bonds, clean energy stocks, and general stocks in global markets around the COVID-19 outbreak. They conclude that the influence of clean energy stocks on general stock markets has grown over time, especially during periods of economic recovery.

Nonetheless, this work diverges from previous related research in two critical aspects. Firstly, it constitutes the first attempt to systematically analyze the presence of explosiveness in the renewable energy equity sectors of the three principal economic regions (the U.S., Europe, and China), while also investigating the potential co-explosivity in renewable energy stock prices across these regions. Secondly, it quantifies the dynamics of connectedness between the regional renewable energy equity sectors and their broader stock markets. Therefore, this research offers a unique opportunity to enhance the understanding of explosive behavior in major renewable energy sectors and provides valuable insights into the interdependencies and potential systemic risks that may arise from the interconnectedness between renewable energy sectors and general stock markets.

4. Methodology

4.1. Detection of price explosiveness

A conventional framework for the analysis of financial bubbles is given by the classical asset pricing model, expressed as:

$$P_t = \sum_{i=0}^{\infty} \left(\frac{1}{1+r_f}\right)^i E_t(D_{t+i}) + B_t \tag{1}$$

where P_t denotes the price of the asset under consideration at time t, D_t is the payoff received from the asset and r_f is the risk-free interest rate ($r_f > 0$). By recursively substituting into Eq.(1), the asset price can be decomposed as:

$$P_t = F_t + B_t \tag{2}$$

where F_t is the fundamental component, determined solely by expected future payoffs, while B_t is the bubble term, which satisfies the submartingale property:

$$E_t(B_{t+1}) = (1 + r_f)B_t \tag{3}$$

This submartingale property implies that the bubble's size is expected to increase in the next period, leading to explosive behavior.

In the absence of bubbles, $P_t = F_t$, implying that the degree of nonstationarity of the asset price is determined by the characteristics of the payoff series, which is generally considered to be at most integrated of order one. However, when bubbles are present, B_t becomes the primary driver of price dynamics, leading to explosive behavior due to its submartingale property. This explosive quality contrasts with the unit root process typically associated with the fundamental component, as D_t is commonly assumed to follow a martingale. Consequently, empirical evidence of explosive behavior in asset prices is often interpreted as a clear indicator of bubble formation.

A variety of econometric techniques, primarily recursive right-tailed unit root tests, have been proposed to detect speculative bubbles and market exuberance (Diba and Grossman, 1988; Phillips and Yu, 2011; Phillips et al., 2011; Homm and Breitung, 2012; Shi, 2013).[2] These tests typically operate under the null hypothesis of no bubbles, implying that asset prices follow a martingale process. The alternative hypothesis posits the presence of speculative bubbles and the explosivity of the process. Among these methodologies, the approach developed by Phillips et al. (2015a,b), widely known as the PSY approach, has become the most popular method for detecting episodes of exuberance in asset prices. The PSY framework utilizes a recursive, evolving algorithm based on the Augmented Dickey-Fuller (ADF) model specification, enabling precise date-stamping of the start and end points of each explosive episode. While originally designed for the identification of speculative bubbles, recent work by Phillips and Shi (2019, 2020) has demonstrated the versatility of the PSY approach to capture both periods of market exuberance and subsequent crashes. Thus, the enhanced version of the PSY method introduced by Phillips and Shi (2019) is employed in this study to examine the existence of explosive behavior within the international renewable energy equity sector.

Within the PSY framework, asset price dynamics during the expansionary phase of a financial bubble is modeled as a mildly explosive process represented by:

$$\log P_t = \delta_T \log P_{t-1} + u_t \tag{4}$$

where u_t are martingale difference sequence innovations, and the autoregressive coefficient $\delta_T = 1 + cT^{-\eta}$ mildly exceeds unity (with $c > 0$ and $\eta \in (0, 1)$). Identifying an explosive episode therefore requires distinguishing a mildly explosive process from a standard martingale process in asset prices.

Phillips and Shi (2019) further expand the data generating process to accurately capture market crashes. They propose that the

[2] As pointed out by Evans (1991) and Pavlidis and Vasilopoulos (2020), standard unit root tests based on time-invariant regression models have extremely low power in detecting explosive episodes when these are interrupted by market crashes. This frequently leads to the spurious finding of stationarity even when the asset price under examination exhibits clear signs of explosivity.

dynamics of asset prices during crisis periods can be represented as a random drift martingale process formulated as:

$$\log P_t = L_t + \log P_{t-1} + u_t \tag{5}$$

where L_t is a random sequence term independent of u_t, which introduces a random drift in the observed price process. This random drift can take various forms, allowing the model to effectively capture the sharp declines characteristic of market collapses.

In the PSY methodology and its variants, detecting market crashes involves distinguishing between a martingale process with a small drift (null hypothesis) and a random-drift martingale process (alternative hypothesis). The hypothesis testing is carried out using an ADF-style regression model, tailored to capture both speculative bubbles and the subsequent correction phases.

$$\Delta P_t = \alpha_{r1,r2} + \beta_{r1,r2} P_{t-1} + \sum\nolimits_{j=1}^{k} \psi_{j,r1,r2} \Delta P_{t-j} + \epsilon_t \tag{6}$$

where P_t denotes the price of the asset examined at time t, k is the lag order, Δ is the first-difference operator and ϵ is again an i.i.d. error term with zero mean and constant variance. In turn, $\alpha_{r1,r2}$, $\beta_{r1,r2}$ and $\psi_{j,r1,r2}$ are regression coefficients. The key parameter of interest is $\beta_{r1,r2}$, which equals to 0 under the null hypothesis (random walk process) and is greater than 0 under the alternative hypothesis (explosive behavior). Moreover, the subscripts r_1 and r_2 denote fractions of the total sample size T that specify the starting and ending points of each subsample period, respectively. The ADF statistic for the subsample spanning from r_1 to r_2, denoted as ADF_{r_1,r_2}, represents the t-statistic associated with the estimated coefficient $\beta_{r1,r2}$.

The Generalized Supremum ADF (GSADF) statistic builds on the ADF-style regression model by iteratively estimating it across various data subsamples in a recursive manner. Specifically, the GSADF statistic varies the endpoint r_2 from r_0 to 1 and the starting point r_1 from 0 to $r_2 - r_0$, where r_0 is the minimum window size required to initiate the test computation. The GSADF statistic represents the supremum of the ADF statistic across all possible ranges of r_1 and r_2 within this double recursive subsample structure:

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} ADF_{r_1,r_2} \tag{7}$$

The rejection of the unit root hypothesis in favor of explosive behavior requires that the GSADF statistic exceeds the right-tailed critical value. The GSADF statistic can be employed to detect explosive behavior across the entire sample period, but it does not determine the origination and termination dates of the explosive episodes. To enable real-time monitoring of market exuberance, Phillips et. al (2015a,b) advocate for the use of the Backward Supremum ADF (BSADF) statistic. The BSADF statistic is applied to a sequence of backward expanding samples, where the endpoint of each sample is fixed at r_2 while the starting point r_1 varies from 0 to$r_2 - r_0$. Mathematically, the BSADF statistic is defined as the supremum value of the sequence of ADF statistics calculated over all permissible ranges of r_1 and r_2:

$$\mathrm{BSADF}_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \mathrm{ADF}_{r_1,r_2} \tag{8}$$

By allowing r_2 to vary, a sequence of BSADF statistics is generated, facilitating the precise identification of both the origination and end dates of explosive periods. According to Phillips et al. (2015a), the origination date $\lfloor T\hat{r}_e \rfloor$ of an explosive episode is defined as the first chronological observation at which the BSADF statistic exceeds the corresponding critical value. In turn, the termination date $\left\lfloor T\hat{r}_f \right\rfloor$ is the first chronological observation after $\lfloor T\hat{r}_e \rfloor + \delta \log(T)$, where the BSADF statistic falls below its critical value. Formally, these dates are determined as follows.

$$\hat{r}_e = \inf_{r_2 \in [r_0,1]} \left\{ r_2 : \mathrm{BSADF}_{r_2}(r_0) > \mathrm{scv}_{\beta_T}(r_2) \right\} \tag{9}$$

$$\hat{r}_f = \inf_{r_2 \in \left\{ \hat{r}_e + \frac{\delta \log(T)}{T}, 1 \right\}} \left\{ r_2 : \mathrm{BSADF}_{r_2}(r_0) < \mathrm{scv}_{\beta_T}(r_2) \right\} \tag{10}$$

where $\mathrm{scv}_{\beta_T}(r_2)$ denotes the $100(1 - \beta_T)$% critical value of the BSADF statistic, with β_T representing the significance level of the test. The minimum duration of an explosive episode is given by δ log(T), with δ being a frequency-dependent parameter.

Harvey et al. (2016) highlighted that heteroskedasticity can compromise the accuracy of right-tailed unit root tests for detecting explosivity, such as the PSY approach. Furthermore, the recursive nature of these tests increases the probability of Type I errors (false positives), exacerbating the problem of multiplicity. To overcome these challenges, Phillips and Shi (2020) developed a novel composite bootstrap method that mitigates the impact of heteroskedasticity and addresses the multiplicity problem inherent in recursive testing, thus reducing the risk of incorrect bubble detection. This composite bootstrap procedure involves several steps, incorporating wild bootstrap to handle heteroskedasticity and replicating the PSY test sequence to account for multiplicity, ultimately generating more reliable critical values for the PSY procedure.

4.2. Co-explosivity analysis

Once episodes of explosive behavior are accurately identified and dated, a critical next step is to examine the phenomenon of co-explosivity, defined as the simultaneous occurrence of explosive dynamics across multiple variables. Due to its simplicity and ease of use, the logistic regression-based framework introduced by Bouri et al. (2019) has become a widely adopted benchmark for quantifying co-explosivity. This approach has been extensively applied in cryptocurrency markets (Chowdhury et al., 2022; Haykir and Yagli, 2022; Shahzad et al., 2022) and stock markets (Aloosh et al., 2022; Yang and Ferrer, 2023; Potrykus et al., 2024). It models the probability of explosivity in one variable as a function of explosive behavior in other variables, providing valuable insights into the interdependencies and systemic dynamic within the dataset. The logit model employed by Bouri et al. (2019) is expressed as follows:

$$\log\left(\frac{P(Y_t = 1X)}{1 - P(Y_t = 1X)}\right) = \beta_0 + \beta_j X_{j,t} + \varepsilon_t \tag{11}$$

where Y_t is a binary variable that takes the value of 1 if $BSADF_{r_2,t} > cv_{\alpha,r_2,t}$, indicating explosive behavior in variable Y at time t, and 0 if $BSADF_{r_2,t} \leq cv_{\alpha,r_2,t}$, implying the absence of explosivity. The term β_0 represents the intercept, while β_j is a vector of logistic regression coefficients associated with the five independent variables (X_j), which are dummy variables constructed exactly in the same manner as the dependent variable. In the present study, each dummy variable captures the explosive dynamics of one of the five equity market indices under investigation. The error term, ϵ_t, is assumed to follow a standard logistic distribution.

4.3. Diebold-Yilmaz connectedness framework

The methodology introduced by Diebold and Yilmaz (2012, 2014) for assessing the magnitude and direction of connectedness among a set of variables has become a cornerstone in financial econometrics. It is grounded in the decomposition of forecast error variance within a Vector Autoregression (VAR) model, where variance decompositions are used to determine the proportion of the H-step-ahead forecast error variance of a variable i that can be attributed to shocks originating from another variable j. This makes it particularly effective for quantifying spillovers, whether in returns or volatilities, and contagion across individual assets, portfolios, or markets. The Diebold-Yilmaz connectedness framework is built on the generalized VAR model proposed by Koop et al. (1996) and Pesaran and Shin (1998) and one of its main advantages lies in its invariance to the ordering of variables in the VAR system. This method has been extensively applied to study connectedness across international stock markets (Gamba-Santamaria et al., 2019; Li, 2021; Li et al., 2021; Wang et al., 2023; Yu et al., 2024), offering key insights into the propagation of shocks across stock markets and the systemic risk during periods of market turmoil.[3]

The Diebold-Yilmaz connectedness approach starts from a covariance stationary N-variable VAR(p) model represented as:

$$X_t = \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t \tag{12}$$

where X_t denotes the $N \times 1$ vector of endogenous variables, ϕ_i are the $N \times N$ autoregressive coefficient matrices, and $\epsilon_t \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances. The moving average representation of the VAR process in Eq. (12) is given by $X_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}$, where the $N \times N$ coefficient matrices A_i obey the recursion $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, with A_0 being an $N \times N$ identity matrix and $A_i = 0$ for i < 0.

The moving average coefficients are crucial to understand the system's dynamics. Variance decompositions enable the forecast error variances of each variable to be split into components attributable to shocks to the other variables in the system.

The H-step-ahead generalized forecast error variance decomposition is computed as follows:

$$d_{gH,ij} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)} \tag{13}$$

where e_j is an $N \times 1$ selection vector with the jth element equal to 1 and all others equal to 0, Σ represents the covariance matrix of the disturbance vector ϵ_t, and σ_{jj} denotes the standard deviation of the disturbance in the jth equation. Thus, $d_{gH,ij}$ quantifies the importance of the jth variable in predicting the ith variable, providing a clear measure of spillovers between them.

In the generalized decomposition framework, the sum of the contributions to the forecast error variance for each variable does not necessarily equal one. To address this, each entry in the variance decomposition matrix can be normalized using the following formula:

[3] There are other methods broadly recognized for their capacity to model the complex, time-varying relationships between assets or markets, with the Dynamic Conditional Correlation-GARCH (DCC-GARCH) model developed by Engle (2002) being one of the most influential and extensively used frameworks. However, the DCC-GARCH approach has several key weaknesses when compared to the Diebold-Yilmaz connectedness framework. One of the principal drawbacks of the DCC-GARCH model is its focus on pairwise conditional correlations, which constrains its ability to capture system-wide spillovers among multiple variables. Furthermore, the DCC-GARCH approach does not provide clear insights into the directionality of spillovers, failing to distinguish between the source and recipient of shocks. In addition, the interpretability of the DCC-GARCH output, especially its dynamic correlations and conditional volatility estimates, is less intuitive compared to the connectedness measures of the Diebold-Yilmaz framework. Finally, as the dimensionality of the system increases, the computational complexity of the DCC-GARCH approach rises exponentially, making it less practical for analyzing large networks of interconnected variables.

$$\widetilde{d}_{gH,ij} = \frac{d_{gH,ij}}{\sum_{j=1}^{N} d_{gH,ij}} \tag{14}$$

This normalization procedure produces a connectedness table, exemplified in Table 1, which facilitates the calculation of key connectedness measures among the variables in the system. Each element of the connectedness table quantifies the pairwise directional connectedness from one variable j to another variable i, denoted as $d_{H,ij} = C_{H_{i\leftarrow j}}$. It is important to note that bidirectional connectedness between two variables is not inherently symmetric, hence $C_{H,i\leftarrow j} \neq C_{H,j\leftarrow i}$. For a more nuanced understanding of the relationships between two variables, the calculation of net connectedness proves beneficial. Thus, the net pairwise directional connectedness is defined as $C_{H,ij} = C_{H,j\leftarrow i} - C_{H,i\leftarrow j}$.

The off-diagonal row and column sums of the connectedness table, termed *"From"* and *"To"*, provide the total directional connectedness measures. The total connectedness from all other variables to a specific variable ***i*** is the sum of all row elements and can be computed as:

$$C_{H_{i\leftarrow \cdot}} = \sum_{j=1, j\neq i}^{N} d_{H,ij} \tag{15}$$

Conversely, the total connectedness from a particular variable ***j*** to all other variables is the sum of all column elements and can be obtained as:

$$C_{H,\cdot\leftarrow j} = \sum_{i=1, i\neq j}^{N} d_{H,ij} \tag{16}$$

Furthermore, the net total directional connectedness can be defined as the difference between the total connectedness *transmitted* to others and the total connectedness *received* from others, represented as $C_{H_i} = C_{H,\cdot\leftarrow i} - C_{H,i\leftarrow \cdot}$. Finally, the grand total of the off-diagonal elements in the connectedness table, obtained by summing either the *"From"* column or the *"To"* row, provides a comprehensive measure of total connectedness within the system. This total connectedness measure is expressed as:

$$C_H = \frac{1}{N}\sum_{i,j=1, i\neq j}^{N} d_{H,ij} \tag{17}$$

Insert Table 1 around here

5. Data

The dataset utilized in this study consists of daily closing prices of stock market indices from three key regions, namely the United States, China, and Europe. For each region, both a renewable energy equity sector index and a general stock market index are analyzed, facilitating a comparative investigation into whether explosive behavior is confined to the renewable energy sector or reflective of broader market dynamics. The three renewable energy stock indices under consideration are the WilderHill Clean Energy Index (ECO) for the United States, the European Renewable Energy Index (ERIX) for Europe, and the CSI China Mainland New Energy Index (CNE) for China. These indices are widely recognized as essential benchmarks for assessing the performance of clean and sustainable energy industries, encompassing diverse sectors like solar power, wind power, hydropower, biofuels, energy storage, and electric vehicles. The ECO index, launched in 2004, was the world's first clean energy stock index, comprising firms listed on major U.S. stock exchanges. Likewise, the ERIX and CNE indices capture the renewable energy ecosystem in Europe and China, respectively. Together, these indices offer a comprehensive view of the global clean and sustainable energy sector.

To gauge broader market trends, the analysis also incorporates three major equity indices, such as the S&P 500 for the U.S., the

Table 1
Schematic of the connectedness table.

					From others
X_1	d_{11}^H	d_{12}^H	$\cdots$	d_{1N}^H	$\sum_{j=1}^{N} d_{1j}^H, j \neq 1$
X_2	d_{21}^H	d_{22}^H	$\cdots$	d_{2N}^H	$\sum_{j=1}^{N} d_{2j}^H, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
X_N	d_{N1}^H	d_{N2}^H	$\cdots$	d_{NN}^H	$\sum_{j=1}^{N} d_{Nj}^H, j \neq N$
To others	$\sum_{i=1}^{N} d_{i1}^H i \neq 1$	$\sum_{i=1}^{N} d_{i2}^H i \neq 2$	$\cdots$	$\sum_{i=1}^{N} d_{iN}^H i \neq N$	$\frac{1}{N}\sum_{i,j=1}^{N} d_{ij}^H i \neq j$
			$\cdots$		

Notes: This table presents a schematic of the main connectedness measures of the Diebold and Yilmaz (2012, 2014) connectedness framework and their relationships. The elements of this table comprise the variance decompositions, also called variance decomposition matrix, for every possible pair of variables. This table also includes a rightmost column with row sums, a bottom row with column sums, and a bottom-right element containing the grand average, in all cases for *i* different from *j*.

Eurostoxx 600 for Europe, and the CSI 300 for China. The S&P 500 is a comprehensive index that tracks the performance of 500 prominent U.S. companies across a wide range of industries, serving as a primary barometer of the overall U.S. stock market. The Euro Stoxx 600 covers 600 leading European companies from both eurozone and non-eurozone economies, offering extensive coverage of European equity markets. Meanwhile, the CSI 300 benchmarks the Chinese stock market by tracking the 300 largest and most liquid companies traded on the Shanghai and Shenzhen stock exchanges. These broader market indices provide critical insights into the macroeconomic health and market trends of their respective regions.

The sample periods for the dataset vary across regions, reflecting differences in the availability of historical data. For Europe, the timeframe spans from April 13, 2004, to April 9, 2024, representing the longest dataset. The U.S. sample runs from November 14, 2013, to April 9, 2024, while the China sample extends from April 24, 2012, to April 9, 2024. These periods encompass several major international events, including the 2008–2009 global financial crisis, the 2015 Chinese stock market crash, the COVID-19 pandemic in 2020, and the ongoing Russia-Ukraine conflict since early 2022. The stock market indices are denominated in their respective local currencies: U.S. dollars for the U.S. equity indices, euros for European indices, and renminbi for Chinese indices. The data was collected from Eikon Refinitiv. Following common practice in the analysis of asset price bubbles, natural logarithms of stock market indices are used for the identification of explosive behavior.

Table 2 presents the descriptive statistics of the daily stock indices in levels over the entire sample period. The renewable energy equity indices exhibit greater volatility, as evidenced by their standard deviations, compared to the broader stock indices. Among the renewable energy indices, the ERIX shows the highest volatility, followed by the ECO and CNE indices. The skewness coefficients of stock market indices do not reveal a consistent pattern of asymmetry. The U.S. stock indices and the CNE index are positively skewed, while the CSI 300 and European stock indices exhibit negative skewness. Moreover, all indices display kurtosis values exceeding 3, suggesting leptokurtic distributions. The Jarque-Bera test statistics corroborate this deviation from normality across all indices, rejecting the null hypothesis of a normal distribution at the 1 % significance level.

6. Empirical results

6.1. Identification of episodes of explosiveness

This section presents the empirical findings from applying the bubble detection method of Phillips and Shi (2019) to the renewable energy equity sector in the three major regions (the U.S., Europe and China). Following the guidelines of Phillips et al. (2015a), the minimum window size, r_0, is determined according to the rule of thumb $r_0 = 0.01 + 1.8/\sqrt{T}$, where T is the total sample length. Consequently, the minimum window size varies across regions due to differences in sample sizes. The optimal lag order of the ADF model in Eq. (6) is selected for each index using the Bayesian Information Criterion (BIC), with a maximum lag order of 10 for each subsample. The selected lag order for the three regional renewable energy equity indices is found to be one. Moreover, the heteroskedasticity- and multiplicity-consistent bootstrap procedure proposed by Phillips and Shi (2020) is employed to obtain robust critical values. The empirical identification of episodes of explosivity in the renewable energy equity sectors is conducted using the *psymonitor* package in R created by Caspi et al. (2018), which implements the optimized recursive method of Phillips and Shi (2019), along with the composite bootstrap technique of Phillips and Shi (2020).

Table 3 displays the GSADF statistics for the three regional renewable energy equity indices, as well as their corresponding broader market counterparts. The GSADF statistic is used to assess the occurrence of at least one episode of explosive dynamics throughout the entire sample period. As can be seen, the null hypothesis of no explosive behavior can be rejected at least at the 5 % significance level for the three regional renewable energy indices, which suggests the presence of periods of explosiveness within the renewable energy equity sectors in all three regions analyzed. However, the evidence of explosiveness is somewhat less clear for the general stock market indices. In particular, while the null hypothesis of no explosivity is rejected at least at the 5 % level for the STOXX 600 and CSI 300 indices, the S&P 500 index does not exhibit explosive behavior over the sample period under scrutiny.

Since the GSADF statistic does not pinpoint the origination and termination dates of explosive episodes, the BSADF statistic is employed for real-time monitoring of market exuberance. Fig. 1 illustrates the temporal evolution of daily indices for renewable energy and broader equity markets, alongside the identified explosive periods lasting at least three months (denoted by the green shaded areas) as determined by the method of Phillips and Shi (2019). This graphical analysis reveals that all examined equity indices,

Table 2
Descriptive statistics of daily stock market indices.

Series	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
SP500	8.66	9.34	8.05	0.36	0.11	4.66	199.47***
ECO	4.38	5.79	3.72	0.48	0.95	6.04	395.37***
STOXX600	6.41	7.11	5.52	0.36	−0.04	4.98	222.35***
ERIX	6.98	8.16	5.60	0.59	−0.20	5.26	148.80***
CSI300	8.36	8.93	7.74	0.30	−0.50	5.23	194.35***
CNE	7.54	8.58	6.71	0.44	0.66	5.47	246.20***

Notes: This table presents the descriptive statistics of daily stock indices (expressed in natural logarithm form) over the full sample period. Mean, Max., Min., and Std. Dev. represent the mean value, maximum value, minimum value, and standard deviation of each index, respectively. In addition, Skewness and Kurtosis refer to the skewness and kurtosis metrics for each time series, while Jarque-Bera is the Jarque-Bera test statistic for normality. As usual, * , ** , and *** denote rejection of the null hypothesis of normal distribution at the 10%, 5%, and 1% significance levels, respectively.

Table 3
GSADF statistics.

Indices	Test statistic	10 %	5 %	1 %
SP500	2.25	2.63	2.94	3.74
ECO	3.69 ***	2.56	2.79	3.39
STOXX 600	2.91 **	2.62	2.90	3.42
ERIX	3.05 **	2.54	2.83	3.41
CSI300	4.40 ***	2.63	2.89	3.54
CNE	3.55 ***	2.49	2.76	3.43

Notes: This table reports the values of the GSADF statistics for the daily renewable energy equity indices and broader stock market indices over the entire sample period. In addition, it also includes the critical values at the 10%, 5%, and 1% significance levels.

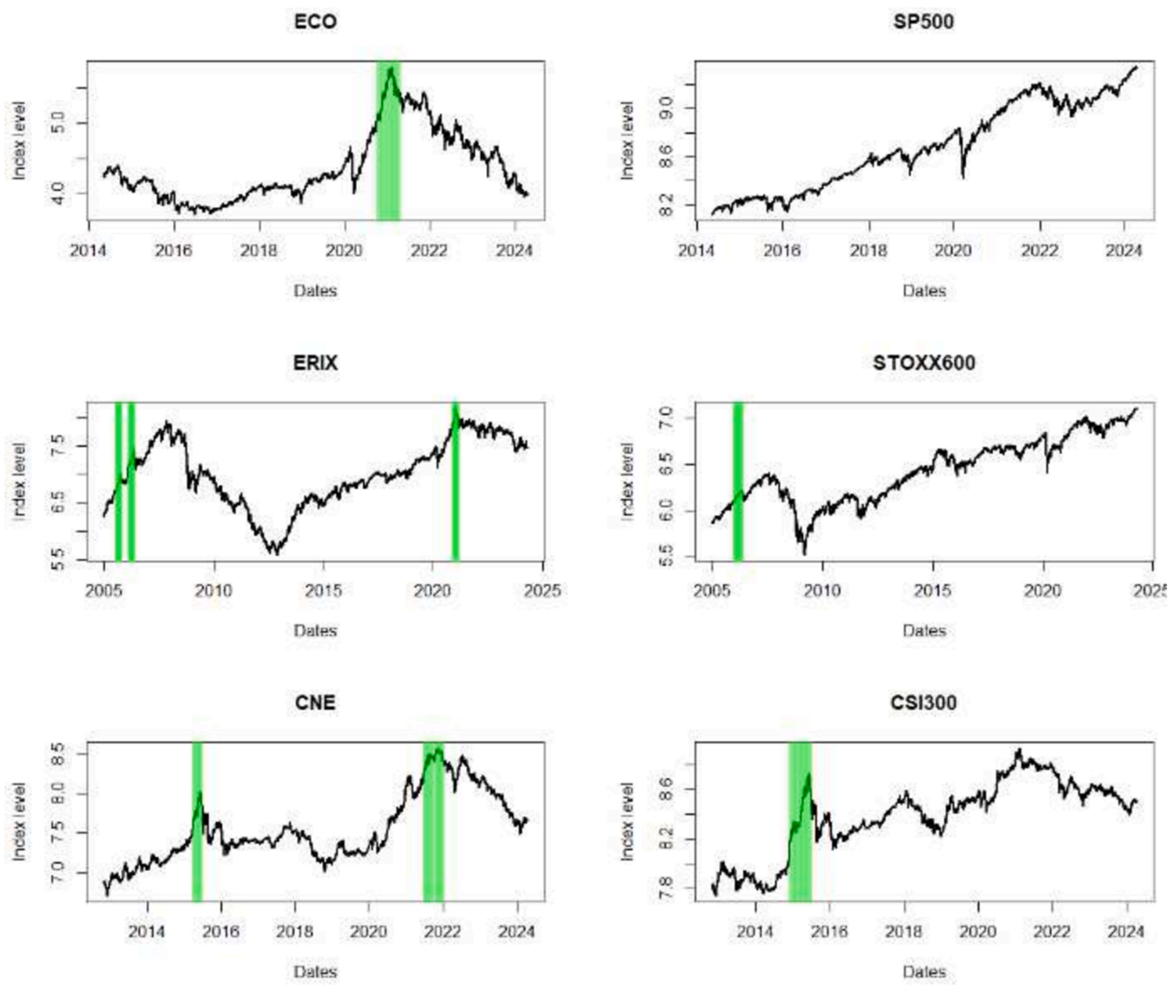

Fig. 1. Explosiveness periods in renewable energy and broader equity market indices.

except for the S&P 500, have experienced periods of explosive behavior throughout the sample period. However, substantial divergences emerge in the timing, magnitude, and duration of these episodes across regions and between the renewable energy sector and broader market indices within each region. Particularly, the renewable energy equity sector demonstrates a stronger propensity for explosiveness compared to the general stock market across all three regions. Another striking aspect is that episodes of explosivity in the broader stock markets of the three regions, if they occurred, took place at least nearly a decade ago, with no temporal overlap. In contrast, there is clear evidence of more recent explosive periods in the renewable energy equity sector across the three regions. These episodes began shortly after the onset of the COVID-19 pandemic and exhibit a significant degree of synchronicity, especially between the U.S. and European renewable energy equity indices, underscoring a sector-wide exuberance driven by post-pandemic dynamics.

Turning to a more granular analysis, Table 4 presents the origination and termination dates for major explosive periods within the regional renewable energy equity indices, each lasting a minimum of three months. For comparison purposes, the corresponding dates

Table 4
Origination and termination dates of episodes of explosiveness.

Indices	Time interval	Duration
SP500	–	–
ECO	2020:M09 – 2021:M04	200
STOXX600	2005:M12 – 2006:M05	162
ERIX	2005:M06 – 2005:M10	112
	2006:M01 – 2006:M05	114
	2020:M11 – 2021:M03	111
CSI300	2014:M11 – 2015:M07	223
CNE	2015:M03 – 2015:M06	100
	2021:M06 – 2022:M01	203

Notes: This table presents the origination and termination dates of each identified episode of explosiveness, along with its respective duration (each lasting a minimum of ninety days), for both renewable energy and broader stock market indices. These dates have been determined using the Phillips and Shi (2019) methodology in conjunction with the heteroskedasticity- and multiplicity-robust bootstrap technique of Phillips and Shi (2020).

for broader market indices are also included. These episodes are identified employing the method developed by Phillips and Shi (2019), enhanced by the composite bootstrap technique introduced by Phillips and Shi (2020).

Firstly, focusing on the U.S. renewable energy sector, the ECO index registered a single explosive episode from September 2020 to April 2021. This surge in U.S. renewable energy stock prices can be attributed to several interrelated factors. On the one hand, the historically low levels of interest rates for a decade following the 2008–2009 global financial crisis greatly benefited companies in the renewable energy sector, which rely heavily on vast amounts of borrowing to cover high upfront capital costs. This prolonged period of artificially low interest rates, driven by quantitative easing, allowed renewable firms to access debt and equity financing at a much lower cost, thus inflating their valuations. Concurrently, the low-rate environment encouraged investors to seek higher returns in riskier assets, including renewable energy equities, further fueling the sector's rapid price appreciation. In parallel, the exponential rise in investing based on environmental, social, and governance (ESG) criteria in recent years bolstered the renewable energy equity sector. The growing recognition of the urgent need for a transition to a more sustainable economy spurred heightened demand for renewable energy equities. The COVID-19 pandemic only intensified this trend, as it drew global attention to sustainability and climate change mitigation, further boosting investor enthusiasm. Market optimism was also fueled by the anticipation of considerable federal support for renewable energy under the Biden administration, contributing to the exuberant valuations observed during this period. Additionally, dramatic cost reductions in key clean technologies enhanced the sector's competitive positioning, making renewable energy even more attractive to investors. Collectively, these factors created an optimal environment for the renewable energy sector, culminating in the explosive episode identified for the ECO index.

The unwinding of this exuberance, marked by the bursting of the U.S. renewable energy bubble at the end of the first quarter of 2021 is primarily linked to the U.S. Federal Reserve's sharp interest rate hikes aimed at curbing inflation. This inflation was driven by post-pandemic supply-chain disruptions, rising commodity prices, and substantial U.S. fiscal stimulus packages in response to the COVID-19 pandemic. Given the capital-intensive nature of the renewable energy sector, higher interest rates significantly elevated the cost of capital, raising serious concerns about the financial viability of many companies in the sector. As these new macroeconomic conditions emerged, investor euphoria quickly evaporated, and renewable energy equities began to be viewed as dangerously overvalued, leading to massive sell-offs and the subsequent collapse in stock prices. Importantly, this episode of exuberance in the U.S. renewable energy equity sector was not accompanied by similar explosive dynamics in the broader U.S. stock market. This evidence is fully consistent with Lehnert (2023), who applied the PSY procedure to identify a recent period of exuberance in U.S. clean energy equities, as captured by the Nasdaq Clean Edge Green Energy index, beginning in mid-2020.

Secondly, the ERIX index, representing the European renewable energy sector, experienced three dictinct episodes of exuberance throughout the sample period. The first two periods of explosiveness occurred in 2005 and 2006, with only a few months separating them. The exceptional performance of European renewable energy stocks during the mid-2000 s can be ascribed to a convergence of factors, including robust growth prospects for the sector, persistently low long-term interest rates, high crude oil prices, and expectations of intensified governmental support for renewable energy initiatives. This early phase of market exuberance is consistent with the Europe's leading role at the forefront of the transition towards a sustainable, fossil fuel-free economy. However, it is worth noting that the boom in the European renewable energy equity sector observed in 2006 also coincided with a period of exuberance in the broader European stock market, as represented by the STOXX 600 index. This suggests that the explosive dynamics of European clean energy stock prices during that period cannot be considered as a phenomenon entirely attributable to the renewable energy sector, but was influenced to some extent by a strong bullish trend in the overall European stock market. Supporting this view, Bohl et al. (2015) identified similar explosive price behavior in the European and global renewable energy sectors during the mid-2000 s, while the U.S. alternative energy sector did not exhibit comparable exuberance. Further corroborating this, Bohl et al. (2013) documented a speculative bubble in German alternative energy stocks between 2004 and 2007, driven by positive investor sentiment and optimism surrounding the sector's long-term prospects. The most recent episode of explosiveness in European renewable energy stocks took place between November 2020 and March 2021, closely mirroring the bubble-like behavior observed in the U.S. ECO index during the same period. As in the U.S. case, this surge in valuations was fueled by a mix of factors including historically low interest rates, supportive government policies promoting the adoption of renewable energy sources (i.e., EU Green Deal), rising demand for environmentally friendly investments due to environmental concerns, and improved cost competitiveness of renewable technology. However, the tightening of monetary policy by the European Central Bank in response to rising inflation across several EU member states significantly worsened the financial landscape for European renewable energy companies. Higher interest rates increased the cost of financing for these capital-intensive firms, dampening investor enthusiasm and acting as a major catalyst for the bursting of the bubble in European clean energy stocks from mid-2021 onward.

Lastly, two periods of explosive dynamics are identified in the CNE index. The first, shorter episode of exuberance occurred between March and June 2015. This surge was not unique to the Chinese renewable energy sector but reflected a broader wave of market euphoria that swept across the entire Chinese stock market, culminating in the well-documented 2015 Chinese stock market disaster. The genesis of this episode of explosivity can be traced to a strongly bullish Chinese stock market driven by a variety of factors. First, the Chinese government actively encouraged retail participation in the stock market, fostering a wave of speculative investment. Second, the People's Bank of China implemented a series of rapid interest rate cuts, which substantially increased investor appetite for higher-yielding assets like equities. Third, the influx of new retail investors, characterized by limited financial education, low risk aversion, a focus on short-term gains, and a high propensity for herd behavior, exacerbated the speculative fervor and amplified the market's upward momentum. Additionally, within the more specific context of the renewable energy sector, supportive policies of the Chinese government were pivotal in nurturing the development of the wind, solar, and hydropower industries. However, by mid-2015, the bubble burst, driven by a confluence of factors. Firstly, the sharp decline in Chinese manufacturing production from early 2015 signaled a weakening economy, revealing a notable disconnection between stock market valuations and underlying macroeconomic fundamentals. Secondly, the reduction in international capital flows into China facilitated the reversal of the bullish trend in the Chinese stock market. Finally, regulatory restrictions on leverage and short-selling among Chinese investors further pushed the stock market collapse, leading to a sharp contraction in equity prices across sectors, including renewable energy. Notably, this episode of exuberance in China's renewable energy sector did not coincide temporally with the explosive dynamics observed in the U.S. and European renewable energy markets, underscoring the view that the 2015 renewable energy bubble in China was part of a broader phenomenon tied to the overall Chinese equity market. In this regard, evident signs of bubble-like behavior in the Chinese alternative energy industries during 2015 were also detected by Wang et al. (2020) and Wang et al. (2024). The Chinese renewable energy equity sector experienced a second phase of explosive growth between June 2021 and January 2022. This later episode appears to reflect a delayed contagion effect from the exuberant dynamics observed in the U.S. and European renewable energy sectors following the onset of the COVID-19 pandemic. Wang et al. (2024) corroborate this finding, noting the presence of explosive dynamics in the Chinese renewable energy sector during the second half of 2021. Interestingly, this period of explosiveness in the renewable energy sector does not overlap with any explosive activity in the broader Chinese equity market, highlighting the sector-specific nature of the 2021 bubble and its independence from broader market trends.

6.2. Results of the co-explosivity analysis

To explore co-explosivity and connectedness among the different equity market indices, it is critical to establish a uniform sample period across all datasets. Based on data availability, the selected common sample period spans from November 14, 2013, to April 8, 2024, ensuring comparability across indices. To avoid distortions arising from market closures, dates corresponding to national holidays in the respective regions were excluded. Table 5 summarizes the results of the co-explosivity analysis, as derived from the estimation of the logistic regression model specified in Eq. (11). This model enables a detailed assessment of whether explosive episodes in one equity market index are associated with similar periods of explosivity in others. The findings indicate generally weak co-explosivity among the equity market indices under scrutiny. Specifically, the probability of occurrence of explosivity in the ECO index increases only when the ERIX index is in an explosive phase. Conversely, explosivity in the STOXX600 index appears to reduce the probability of explosivity in the ECO index. Similarly, explosivity in the ERIX index is positively associated with explosivity in the ECO index but negatively influenced by explosivity in the SP500 and STOXX600 indices. In contrast, the CNE index exhibits the least sensitivity to explosivity in the other indices. Its probability of explosivity does not increase with episodes of explosivity in any of the other two regional renewable energy indices. Moreover, explosivity in the SP500 and STOXX600 indices further reduces the likelihood of explosivity in the CNE index. Additionally, the probability of explosivity in the broader SP500, STOXX600, and CSI300 stock indices is not positively affected by the presence of explosivity in the three regional renewable energy indices. The strongest co-explosivity is observed between the ECO and ERIX indices, indicating a notable connection in their explosive dynamics. On the contrary, the bubble-like behavior of the CNE index appears to be entirely independent of the explosive dynamics of U.S. and European renewable energy indices. This limited evidence of co-explosivity, both among the regional renewable energy equity indices and between the renewable energy and general stock market indices, suggests that the explosive dynamics in renewable energy equities is largely a sector-specific phenomenon and does not pose a significant risk of contagion to broader stock markets.

However, it is worth noting that estimating a logit model using time series data, as in the present study, has several potential issues. First, time series data often violate the assumption of independent observations inherent to logistic regression. Temporal dependence among observations can result in biased or inefficient estimates, undermining the reliability of the logit model's predictions (Cameron and Trivedi, 2005). Second, time series data are also prone to autocorrelation, where errors exhibit persistence over time. Since the logit model assumes uncorrelated error terms, failure to address autocorrelation can distort estimated relationships between variables, leading to flawed inferences (Klingenberg, 2008; Wu and Cui, 2014). To overcome these limitations and ensure the robustness of the results, it is critical to complement the logistic regression-based co-explosivity analysis with an alternative method designed for similar purposes. To that end, the panel recursive unit root testing procedure introduced by Pavlidis et al. (2016) is employed in this study.

Table 5
Co-explosivity among equity market indices.

Series	SP500	ECO	STOXX600	ERIX	CSI300	CNE
SP500	–	0.55	−17.40***	−15.53***	2.55**	−16.98***
ECO	0.14	–	−13.19***	3.78***	−0.91	0.97
STOXX600	−17.66***	−15.30***	–	−14.42***	1.95*	−2.46**
ERIX	−14.74***	3.78***	−13.93***	–	−0.72	0.61
CSI300	2.52**	−0.85	1.98**	−0.55	–	1.43
CNE	−15.53***	0.94	−2.50**	0.54	1.43	–

Notes: This table presents the coefficient estimates of the logistic regression model outlined in Eq. (13), utilizing each equity market index as the dependent variable. The dependent variable is a dummy variable taking the value of 1 if the BSADF statistic in *t* for a given equity index exceeds the 5% critical value, indicating a period of explosiveness, and 0 otherwise. The explanatory variables consist of dummy variables constructed in the same manner as the dependent variable for each of the remaining five equity indices. The symbols * , ** , and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

This approach extends the conventional univariate GSADF and BSADF statistics to a panel setting, enabling the identification and dating of episodes of collective explosivity. In essence, the panel approach of Pavlidis et al. (2016) is based on the construction of a measure of overall exuberance by averaging the individual BSADF statistics at each time period.[4] The distribution of this panel unit root test is not invariant to the cross-sectional dependence of the error terms. To deal with that, Pavlidis et al. (2016) adopt a sieve bootstrap procedure to draw robust statistical inference. Analogously to the univariate BSADF framework, dating episodes of common explosivity involves comparing the panel BSADF statistics with the critical values derived from the sieve bootstrap method.[5]

The sequence of panel BSADF statistics depicted in Fig. 2 clearly shows that this panel statistic exceeds its 95 % bootstrapped critical value only during brief and isolated time intervals. In fact, the two longest episodes of general explosivity are concentrated within a very specific timeframe, spanning late 2020 to September 2021, each lasting fewer than 80 days. These findings contradict the notion of prolonged, synchronized episodes of exuberance affecting major regional broader stock markets and renewable energy equity sectors. Instead, they emphasize the transient and fragmented nature of explosive dynamics within these markets. Furthermore, this evidence fully aligns with the limited co-explosivity previously observed in the logistic regression analysis, reinforcing the argument that periods of widespread market exuberance are both short-lived and localized.

6.3. *Results of the connectedness analysis*

This section presents the empirical findings from the analysis of connectedness between the returns of regional renewable energy equity indices and their respective broader stock market indices using the Diebold-Yilmaz connectedness framework. Table 6 summarizes the results of the static connectedness analysis across the six equity indices over the full sample period. Return spillover estimates are derived from a VAR model of order 2, selected based on the Akaike information criterion. In line with Diebold and Yilmaz (2012, 2014), generalized variance decompositions of 10-day-ahead forecast errors are utilized.

9The total connectedness index is 46.42 %, indicating a significant level of interconnectedness among the six equity indices throughout the sample period. Notably, the SP500 index shows the highest degree of connectedness, in terms of both return spillovers transmitted and received, followed by the STOXX600 and ECO indices. These results underscore the U.S. equity market's pivotal role as a primary transmitter of market information, influencing both global market dynamics and the renewable energy sector. As expected, the strongest pairwise connectedness is observed between the broader stock market index and the corresponding renewable energy equity index within each region.

In contrast, the Chinese CNE and CSI 300 indices exhibit the lowest levels of connectedness with the other indices on average. Remarkably, outside the main diagonal of Table 6, which reflects the forecast error variance of a variable attributed to shocks to the same variable, the highest pairwise connectedness measures emerge between the two Chinese equity indices ($C^H_{CNE \leftarrow CSI300 = 33.88\%}$& $C^H_{CSI300 \leftarrow CNE = 32.81\%}$). When considering the diagonal elements for both Chinese indices, it becomes apparent that more than 90 % of the forecast errors can be explained by shocks to the two Chinese indices, with marginal contributions from the other indices. Similarly, the influence exerted by Chinese equity indices on their U.S. and European counterparts is minimal. This evidence reveals the insulated nature of Chinese equity indices from their Western (U.S. and European) counterparts. This insulation can be attributed to the unique characteristics inherent in the Chinese stock market, including a high proportion of retail investors, limited participation of foreign investors, a strong presence of state-owned companies, and notable restrictions on stock tradability (Yang and Ferrer, 2023). In terms of net connectedness, the SP500 and STOXX600 indices emerge as the main transmitters of return spillovers, while the ERIX and CNE indices are the primary receivers.

While the static connectedness analysis offers a useful characterization of the *"average"* or *"unconditional"* connectedness over the sample period, it does not capture potential changes in the strength or direction of interdependence over time. To address this

[4] For technical details of the panel unit root testing procedure, see the original papers by Pavlidis et al. (2016) and Vasilopoulos and Pavlidis (2022).

[5] All calculations of the panel unit root testing procedure of Pavlidis et al. (2016) have been performed using the *exuber* package in R developed by Vasilopoulos et al. (2023).

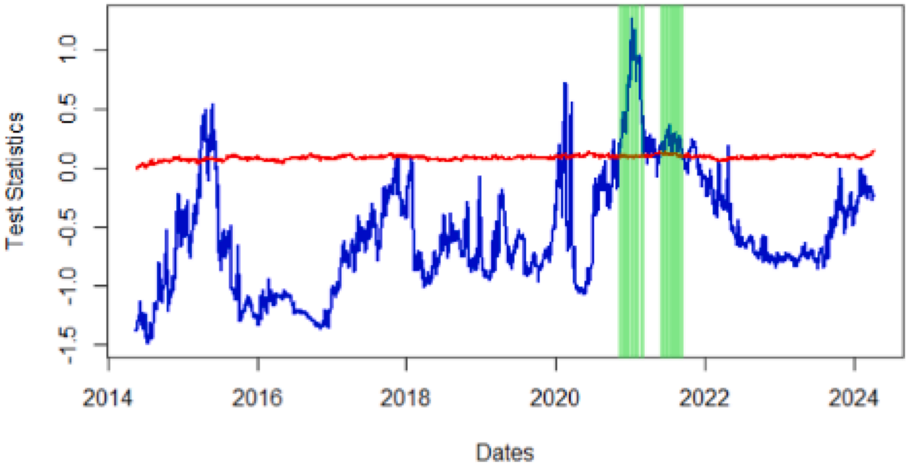

Fig. 2. Date-stamping periods of overall explosivity in broader and renewable energy induces.

Table 6
Static connectedness.

	SP500	ECO	STOXX600	ERIX	CSI300	CNE	From others
SP500	49.13	20.32	19.97	8.15	1.47	0.96	50.87
ECO	22.09	52.40	11.24	10.99	1.69	1.59	47.60
STOXX600	20.38	11.04	48.04	17.43	2.11	1.00	51.96
ERIX	9.61	12.62	20.12	56.07	0.84	0.74	43.93
CSI300	3.03	2.92	3.22	1.12	57.00	32.71	43.00
CNE	1.87	2.63	1.57	1.18	33.88	58.87	41.13
To others	56.98	49.53	56.12	38.87	39.99	37.00	**46.42**
Net	6.11	1.93	4.16	−5.06	−3.01	−4.13	

Notes: This table shows the average total directional connectedness among the six equity market indices under consideration across the full sample period (November 14, 2013, to April 8, 2024) using a forecast horizon of 10 days. The *ij*th entry of this connectedness table represents the *ij*th pairwise directional connectedness, i.e., the percent of the 10-day-ahead forecast error variance of index *i* due to shocks to index *j*. The "From others" column is the row sum (excluding the diagonal entries) that gives total directional connectedness from all other indices to index *i*. The "To others" row provides total directional connectedness from index *j* to all other indices. The bottom "Net" row reflects the difference between the "To others" row and the "From others" column and shows the net total directional connectedness from index *i* to the others. The bottom-right element (in boldface) denotes total connectedness, calculated as the average of the "To others" row or, equivalently, the "From others" column, among the six equity indices.

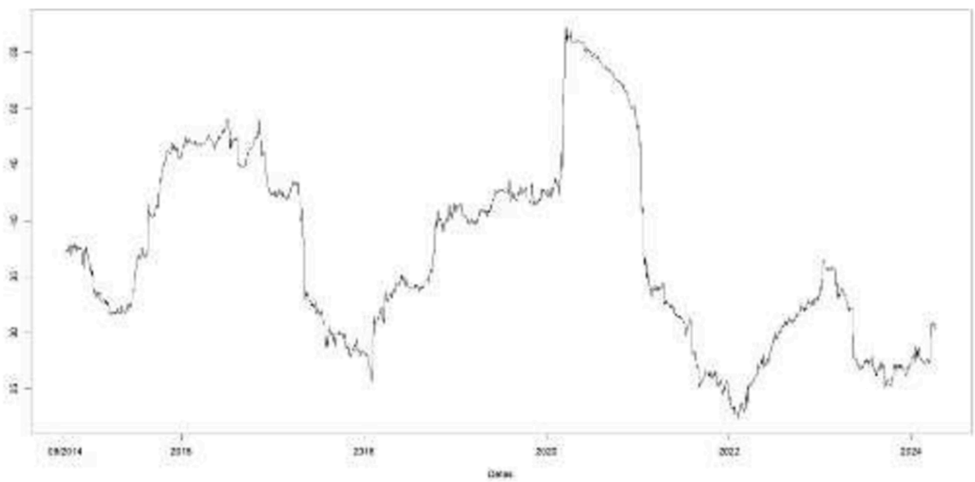

Fig. 3. Dynamic total return connectedness.

limitation, a dynamic connectedness analysis based on a rolling-window estimation is conducted. Fig. 3 depicts the temporal evolution of total return connectedness using a 200-day rolling window and a forecast horizon of 10 days.

The total return connectedness index exhibits significant variation, fluctuating between 25 % and 50 %, which indicates a moderately high level of market interdependence. Two main phases of heightened connectedness stand out. The first phase, spanning from October 2015 to April 2017, is marked by relatively stable values around 45 % for the total return connectedness index. This period coincides with the adoption and early implementation of the 2015 Paris Climate Agreement, which established ambitious global climate goals. This landmark agreement sparked increased interest in the renewable energy sector, boosting the performance of renewable energy stocks and enhancing their interconnectedness with broader stock markets. The second, and most pronounced, phase of elevated connectedness started in March 2020 and extended through early 2021. During this period, the total return connectedness index hit an all-time high of 57.32 % in mid-March 2020, coinciding with the global onset of the COVID-19 pandemic. As governments worldwide declared states of emergency and markets reacted to the economic fallout, the heightened volatility and uncertainty led to an exceptional surge in market interdependence. However, by January 2021, total connectedness began to decline sharply, reaching a sample low of 20 % by early 2022. One possible explanation for this dramatic decrease in connectedness is the decoupling between the renewable energy equity sector and broader stock markets driven by the final stage of the expansionary phase of the bubble in U.S. and European renewable energy stocks during 2020–2021.

Additionally, since mid-2023, total return connectedness has remained relatively low compared to previous years. This reduced interdependence can largely be attributed to the recent underperformance of renewable energy stocks relative to the overall stock market, influenced by several macroeconomic and geopolitical factors. Firstly, the rapid and sharp rises in interest rates since 2022, implemented to curb inflationary pressures post-pandemic, have had a particularly detrimental impact on renewable energy companies, which are typically capital-intensive and highly leveraged. Secondly, in response to the Russia-Ukraine war, many European nations have pivoted towards nuclear energy and coal to lessen their dependence on Russian gas and crude oil. This strategic energy shift has temporarily overshadowed renewables, leading to weaker renewable energy stock performance. Thirdly, growing concerns that the European Union may delay some of its climate targets due to the energy crisis triggered by the conflict in Ukraine have further dampened investor confidence in the renewable energy sector's growth trajectory. These factors collectively have weakened the sector's performance, contributing to a decline in its connectedness with the broader stock market.

Next, we analyze the dynamics of net directional connectedness between each equity index and the others to identify the main net transmitters and receivers of return spillovers. Fig. 4 provides a visual representation of the time-varying net directional return spillovers among the six equity indices under examination over the sample period. Notably, the SP500 index is by far the principal net transmitter of return spillovers to the remaining equity indices, followed by the ECO and STOXX600 indices. On the contrary, the CSI300, CNE, and ERIX indices predominantly function as net receivers of return spillovers for most of the sample period under study. These results are entirely consistent with the earlier findings from the static connectedness analysis, reinforcing the critical role of U.S. equity indices, both the broader stock market index and the renewable energy equity index, as central transmitters of shocks to other regional markets. Furthermore, these results enable a clear distinction between the regional renewable energy equity indices concerning their role in the transmission of shocks. Specifically, the U.S. ECO index is identified as a net transmitter of market information, whereas the Chinese CNE and European ERIX indices primarily serve as net receivers, absorbing external influences rather than driving

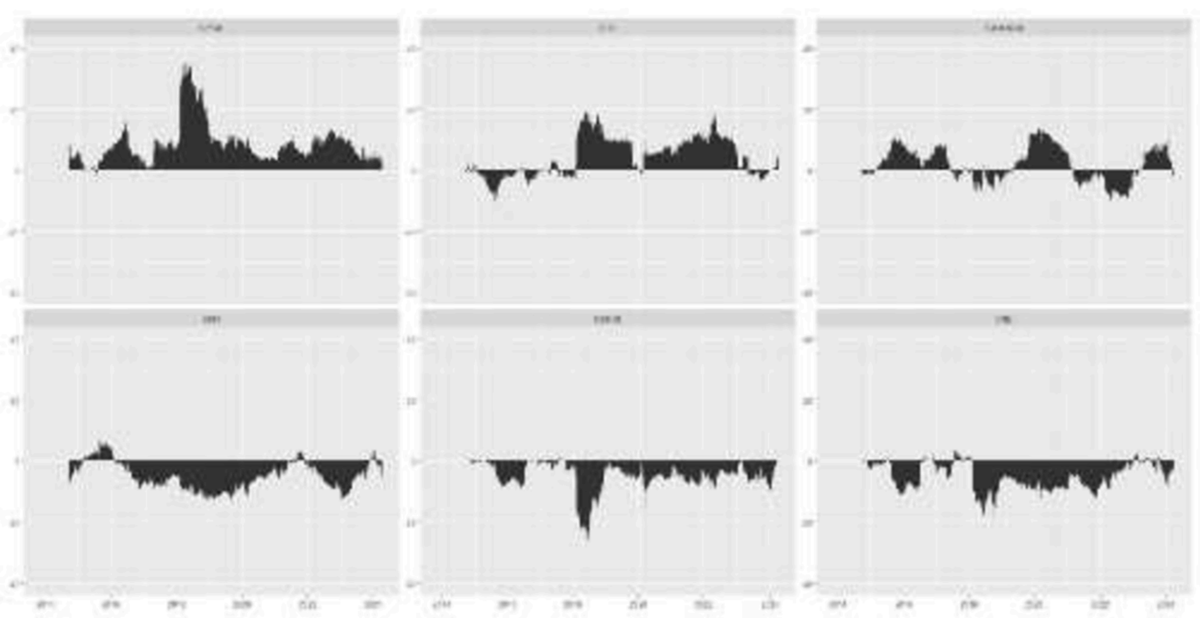

Fig. 4. Dynamic net directional connectedness.

market dynamics.

To shed some light on potential shifts in the pattern of directional connectedness during the recent expansion of the international renewable energy equity sector, Fig. 5 provides network graphs depicting pairwise directional return spillovers among regional equity indices. These graphs compare the entire sample period (November 14, 2013, to April 8, 2024) with the recent period of explosive growth in the renewable energy sector (September 2, 2020, to January 28, 2022). Green nodes represent equity indices that are primarily transmitters of spillovers, while red nodes signify net receivers of pairwise directional return spillovers. The thickness of the connecting edges is proportional to the intensity of pairwise return spillovers. Visual inspection reveals that both the number and intensity of significant spillovers are greater across the full sample period compared to the renewable energy bubble sub-period. This suggests that the recent surge in the sector led to a decoupling of renewable energy equities from broader stock markets, reducing connectedness between renewable energy and general equity markets worldwide. Notably, the U.S. S&P 500 and ECO indices emerge as the key transmitters of return spillovers regardless of the time period analyzed, highlighting their pivotal role in the global equity landscape. Among European indices, the ERIX consistently acts as a net receiver of spillovers, while the STOXX600 shifts from being a net transmitter during the full period to a net receiver during the recent bubble period, signaling evolving market dynamics within Europe. Meanwhile, Chinese equity indices remain largely insulated from their Western counterparts, showing limited connectedness with U.S. and European markets in both periods. This persistent isolation underscores the structural uniqueness of China's equity market its relatively low integration with global financial markets.

7. Conclusions

The exponential growth witnessed in the renewable energy sector in recent years has generated considerable interest within the financial community regarding the occurrence of episodes of price explosiveness in renewable energy stocks on a global scale. Against this backdrop, this work builds upon existing research by investigating the presence of explosive behavior in the renewable energy equity sectors across three major economic regions, namely the United States, China, and Europe. For this purpose, the methodology proposed by Phillips and Shi (2019), which enables detecting both market expansions and collapses, is utilized in tandem with the composite bootstrap technique designed by Phillips and Shi (2020), which, in turn, addresses heteroskedasticity and multiplicity issues inherent in recursive testing. Furthermore, this study incorporates a connectedness analysis using the framework developed by Diebold and Yilmaz (2012, 2014) to assess the degree of interdependence between regional renewable energy sectors and their respective broader stock counterparts.

Our empirical findings unveil the existence of significant periods of explosivity in renewable energy stocks across all three regions during the sample period under scrutiny. Notably, the renewable energy equity sector demonstrates a higher propensity for explosive dynamics compared to the general stock markets within these regions. The most prominent episode of explosiveness occurred between late 2020 and mid-2021 in both the U.S. and European renewable energy sectors, with a similar trend emerging in the Chinese renewable energy sector a few months later. This global surge in alternative energy stocks following the initial wave of the COVID-19 pandemic can be explained by various factors. In particular, the pandemic catalyzed an increased focus on sustainability and environmental issues, igniting a wave of investor enthusiasm for renewable energy, which propelled renewable energy stock prices to historic peaks. In addition, extraordinarily low interest rates, government policies promoting renewable energy development, and declining costs of clean energy technologies also significantly fueled bullish sentiment surrounding renewable energy stocks. However, the anticipation of rising interest rates to combat the inflationary pressures stemming from the COVID-19 crisis played a critical role in the subsequent bursting of the renewable energy bubble. This shift in economic conditions raised serious doubts about the future viability of renewable energy companies, abruptly ending the enthusiastic market sentiment and precipitating a massive sell-off in renewable energy stocks that ultimately caused the bubble to collapse. Overall, there is weak co-explosivity both among the regional renewable energy equity sectors and between these sectors and the broader stock markets, with the notable exception of strong co-explosivity between the U.S. and European renewable energy sectors. This suggests that explosive episodes in renewable energy stocks are primarily sector-specific, with minimal risk of contagion to the general equity markets.

The connectedness analysis further reveals significant return spillovers between the regional renewable energy equity sectors and their broader stock markets throughout the sample period. The most pronounced return spillovers occurred in 2020, driven by heightened economic uncertainty and financial volatility triggered by the outbreak of the COVID-19 pandemic. Throughout the entire sample period, the U.S. general stock market and, to a lesser extent, the U.S. renewable energy equity sector and the European general stock market, act as net transmitters of return spillovers. Conversely, the Chinese broader stock market and the renewable energy sectors in Europe and China serve as net receivers of spillovers. This evidence supports the notion that regional renewable energy equity sectors do not pose a significant threat of systemic risk to global stock markets. The reduced number and intensity of return spillovers during the recent episode of explosivity in the global renewable energy equity sector reflect a decoupling of renewable energy stocks from broader equity markets, particularly visible in the final phase of the renewable energy bubble.

As the renewable energy sector is likely to continue to grow substantially in the coming years, it is essential for policymakers to establish advanced early warning systems designed to detect or predict potential explosive episodes in renewable energy stocks before they spiral out of control. For investors, stable and supportive legislation that promotes long-term investment in clean energy stocks can help mitigate herd behavior and foster investment-oriented strategies. Such measures can prevent speculative bubbles that could disrupt the transition to a greener economy. Importantly, while bubbles in the renewable energy sector may pose risks, they also hold the potential to significantly accelerate technological innovation and the widespread adoption of clean energy technologies, thus positively impacting economic growth and the fight against climate change, an idea encapsulated in the *"social bubble hypothesis"*.

This study advances the state of the art by offering a comprehensive international perspective on price explosiveness in renewable

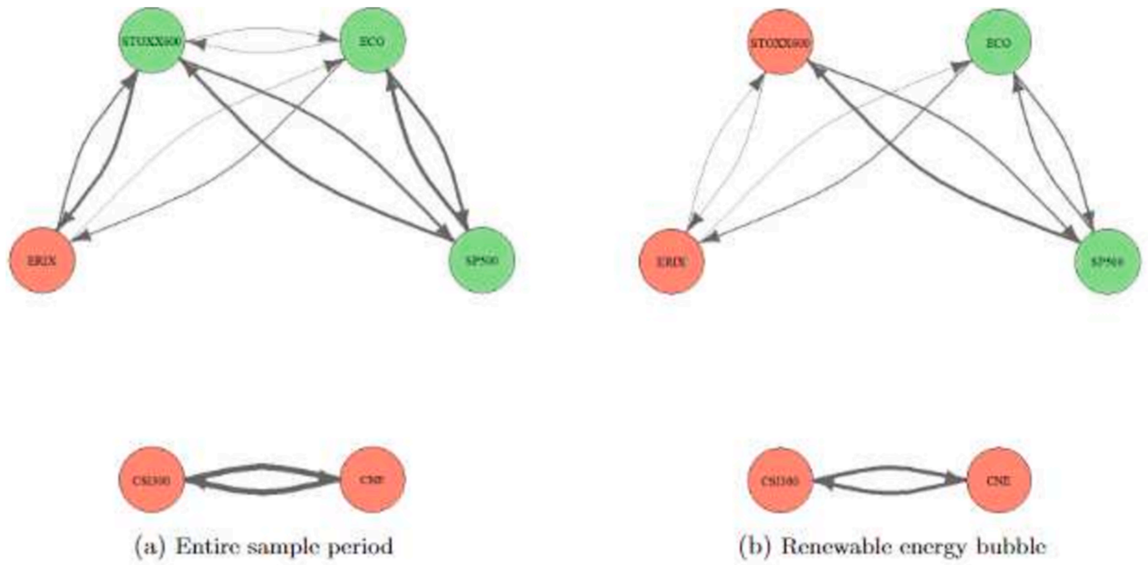

Fig. 5. Network graphys of pairwise directional spillovers.

energy stocks, an area that has been relatively underexplored in previous research. Despite this contribution, some limitations remain, particularly regarding the application of explosive period detection to future price predictions. A potential avenue for future research could be to extend the analysis to other emerging markets whose renewable energy sectors show promising growth prospects. Furthermore, integrating predictive models based on machine learning could yield valuable insights into forecasting explosive periods and their implications for global markets.

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CRediT authorship contribution statement

Juan Ariza: Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Román Ferrer:** Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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