Highlights

Green bubble detection and propagation in the energy market

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- Highlighting the importance of the social bubble hypothesis in the context of the renewable energy sectors.
- A novel perspective on detecting speculative bubbles.
- Offering insights into the potential propagation effects of green bubbles on the stability of the financial system, with possible *"Climate Minsky"* moments.
- Emphasizing the significance of psychological and sociological factors to predict future dynamics in the renewable energy market.

Green bubble detection and propagation in the energy market

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ABSTRACT

Climate change has emerged as a significant global concern, attracting increasing attention worldwide. Following the Great Recession, the term *"Green Bubble"* emerged in academic literature, denoting situations marked by excessive investments in renewable energy sources. While these phenomena can be examined through a social bubble hypothesis, it is essential not to neglect a *"Climate Minsky"* moment triggered by sudden asset price changes. The recent boom in green investing highlights the importance of having an exhaustive understanding of such phenomena. Consequently, this article aims to investigate bubble stages within the renewable energy sector. It presents a novel perspective on bubble detection and investigates the potential propagation effects on the stability of the financial system through econometric models. By exploring bubble dynamics, this research provides relevant policy implications. Drawing inspiration from Joseph Schumpeter's ideas on business cycles, the existence of green bubbles should be recognized as a *"necessary evil"* for the successful transition to a greener future.

1. Introduction

At the dawn of the new millennium, climate change emerged as a significant global phenomenon. In response, numerous researchers have conducted several studies to gain a deeper understanding of the correlations between climate change-related risks and asset prices (Salisu, Ndako and Vo 2023; Gupta and Pierdzioch 2021; Faccini, Matin and Skiadopoulos 2023; Barnett, Brock and Hansen 2020; Barnett 2023). As coined by Giglio, Kelly and Stroebel (2021), these research activities generated a novel field known as *"Climate finance"*, with two main branches. The first is concentrated on climate impacts and their predictive capabilities, while the second is focused on asset pricing changes due to climate-related events. Regarding the prevalent asset pricing theory, the market price of a financial asset reflects the anticipated net present value of its future payoffs. Consequently, the price is conditional on the general expectations that individuals hold for the future, which are driven by both exogenous and endogenous shocks. Global warming can lead to changes in the assets of some of the largest companies resulting in financing problems. On the other hand, the valuation of green companies could see an increasing rise in investment, exceeding their net asset values. As a consequence, a period of financial instability may rise; i.e. when the financial sector is not in perfect sync with the real economy, making the entire system vulnerable to an inevitable *"domino effect"*. Carney (2016) outlined as a transition to a low carbon economy may generate a shock of some market values, causing a *"Climate Minsky"* moment. As a result, financial authorities bear the responsibility of monitoring the financial system to detect potential risks in a timely manner and determining the necessary actions to prevent adverse consequences.

Following the Great Recession, a term known as the *"Green Bubble"* (Wimmer, 2015; Nordhaus and Shellenberger, 2009) started to gain popularity in academic literature, referring to a situation where the world is over-investing in environmentally-friendly assets. In the last decade, there was a notable boost and subsequent contraction in capital investments within the renewable energy market. From 2005 to 2008, the share of investments going to clean energy technologies was more than tripled before a substantial collapse in the following years (Van den Heuvel and Popp, 2022). Notably, the speculative sentiment surrounding investments in clean technology may have been the consequence of an increasing sensibilization on climate change (Giorgis, Huber and Sornette, 2022) and the emergence of new technologies (Van den Heuvel and Popp, 2022). Thus, numerous studies have revealed a meaningful relationship between clean energy, high technology stocks, and oil prices (Kassouri, Kacou and Alola, 2021). However, the true impact of a new green bubble is still being explored. Ghosh, Papathanasiou, Dar and Kenourgios (2022b); Ghosh, Papathanasiou, Dar and Gravas (2022a) argued that not all finance bubbles are harmful to the economic system, and defined green bubbles under a social bubble hypothesis. They suggested that these bubbles can accelerate investment activities in green energy, supporting the ecological transition and combating climate change. Nevertheless, these positive outcomes do not come without costs. Borio, Claessens and Tarashev (2023); Bendixen (2022) claimed that the risk of a green bubble is not insignificant. Investors have genuine incentives to create bubbles, and private agents are already awaiting some form of public support for eco-investing. However, excessive market behaviour is detrimental not only in terms of financial stability but also to the credibility of the transition process. As highlighted in Schumpeter's work on creative destruction in the 1930s (Schumpeter and Backhaus, 2003), effective innovation management is crucial for economic development and recovery.

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Recently, Aversa (2023) conducted a review using text analytics on the topics of scenario analysis and climate change, emphasizing the need for improvements in the modelling, as well as further research on the formation of possible *"Climate Minsky"* moments. From this standpoint, this article has its place in detecting and comprehending emerging bubbles within the renewable energy market. It provides a novel perspective to identifying speculative bubbles, highlighting the importance of climate change sentiment in predicting future market dynamics. Additionally, this analysis offers valuable insights into the potential formation of *"Climate Minsky"* moments during the ecological transition.

The structure of the ongoing analysis is the following. Section 2 aims to offer a comprehensive literature review. In Section 3, a notable distinction between euphoric behaviours and the overall processes behind a speculative bubble is presented. Section 4 will outline the importance of psychological and sociological factors to predict future dynamics within the renewable energy market. Employing an econometric framework, Section 5 is dedicated to investigate the formation of possible *"Climate Minsky"* moments, providing relevant policy implications in terms of financial stability. Section 6 will conclude, summarising the results.

2. Literature Review

The proposed literature review will explore various interconnected fields.

2.1. Speculative bubble

Financial bubbles can be seen as outcomes of market forces (Blanchard and Watson, 1982). Garber (2001) characterized bubbles as a vague concept, suggesting that they involve price movements that cannot be fully explained. He also emphasized how comprehending bubbles is a challenging task since they are events that include financial, economic, and psychological factors. The general equilibrium model proposed by Pástor and Veronesi (2009) predicted that during technological revolutions, stock values of innovative companies may experience bubble phenomena. Similarly, Pástor and Veronesi (2009) argued that the recent boom-bust cycles, such as the dot-com bubble, and the global financial crisis, are two separate aspects of a single phenomenon. The first stage is rooted in technological innovations, while the second cycle is driven by financial innovations. These occurrences are inherent to the progression and assimilation of successive technological revolutions in the market economy. In the face of climate change challenges, Aghion, Veugelers and Serre (2009) emphasized the significance of pushing toward clean-technology-related innovations. They argued that public intervention and incentives for private green innovation are essential to face global warming. Quinn and Turner (2020) proposed a concept called the *"bubble triangle"*, as a warning against excessive market exuberance. Other recent articles, defined green bubbles under a social bubble lens (Giorgis et al., 2022; Ghosh et al., 2022a,b). However, the risk of excessive market growth and large speculative activities puts financial stability at serious risk. To minimize exposure to high-risk situations, it becomes essential to adopt a critical and rational perspective when assessing the true nature of green bubbles (Borio et al., 2023). Joseph A. Schumpeter, an Austrian economist of the 20^{th} century, is known for his theory of innovation and economic growth (Andersen, 2011). According to Schumpeter, economic growth does not happen in a linear way, but through waves of economic change driven by technological innovations. Schumpeter has substantially adapted Kondratiev's wave theory, arguing that scientific and technological progress are the main engine of the economic cycle. In this perspective, new technologies lead to a phase of expansion of the economy, increasing productivity and economic opportunities. This positive expansion continues to a saturation point, in which new technologies become the standard to follow. Failing to give a boost to the economy, a phase of crisis inexorably starts. For Schumpeter, the economic cycle would be the result of specific market forces that promote innovation, which eventually also leads to the development of speculative bubbles and the need for an inevitable correction cycle.

2.2. Bubble detection

As detailed in the work of Boubaker, Liu, Sui and Zhai (2022), methods to identify bubble phases fall into three main categories. The first involves theoretical approaches, which utilize models based on the rational expectations assumption of investors. Alternatively, mathematical procedures employ stochastic analysis to establish a numeric definition of a bubble, often by associating it with deviations from a real martingale process. Empirical methods, on the other hand, encompass hybrid and statistical approaches. In this last category, bubble detection is typically reformulated in terms of explosive behaviours. A large contribution came by Phillips, Wu and Yu (2011); Phillips and Yu (2011); Phillips, Shi and Yu (2015a,b); Phillips and Shi (2020), which provided a series of papers introducing novel right-tailed unit root tests for market exuberance (i.e., the Supremum Augmented Dickey-Fuller test, and its extensions). These right-tailed unit root tests are widely utilized to detect speculative behaviours in various econometric studies. Quite recently, Monschang and Wilfling (2021) investigated the performance and suitability of the Supremum Augmented Dickey-Fuller (SADF), and its extensions on such a task. Using Monte Carlo simulations, it was discovered that the majority of the tests display considerable size distortions when the data-generating process is affected by leverage effects. Furthermore, the results obtained from date-stamping can be highly influenced by the selected data frequency. Despite the probabilistic background of the test being mathematically rigorous, leading to an important contribution to the econometric literature, Monschang and Wilfling (2021) concluded that statistical tests for explosiveness cannot be universally regarded as a tool for bubble detection. Enoksen, Landsnes, Lučivjanská and Molnár (2020) found that bubbles in cryptocurrency markets share common features, such as high volatility regimes, high trading volumes, and high transaction activities. Adopting a fixed-sampled Cumulative Sum control chart (CUSUM), Boubaker et al. (2022) proposed a new method for detecting the timing of bubble bursts in global stock markets. However, drawing from rational expectations theories (Blanchard and Watson, 1982), bubbles are recognized to have distinct phases: formation, burst, and decline. Consequently, the identification of the overall dynamics behind a speculative bubble requires distinct analytical tools.

2.3. Climate Minsky moment

Following the great financial crisis, Minsky's financial instability hypothesis gained popularity in the academic literature (Minsky, 1983). He identified three distinct stages of borrowing and lending that contribute to market instability: hedge, speculative and ponzi. As the financial system moves ahead among these three stages, it becomes increasingly fragile and susceptible to triggering a financial crisis. Such crises often lead to economic downturns and require interventions from policymakers to stabilize the economic system. In this view, the relationship between a speculative bubble and a Minsky moment is closely linked. In essence, speculative bubbles are characterized by irrational exuberance and inflated asset prices, which are the main triggers of a Minsky moment.

Carney (2016) did not negate the possibility of a Minsky moment during the transition to a low-carbon economy, coning the concept of *"Climate Minsky"* moment. Under specific economic assumptions, Bendixen (2022); Kyriacou (2022) outlined how the shift towards a low-carbon economy could potentially lead to the occurrence of *"Climate Minsky"* moments. Such pioneering studies opened the path to a new line of research, in the field of *"Climate Finance"* (Giglio et al., 2021).

Several articles outlined how Google Trends data provides a valid source of information for predicting macroeconomic variables (Qureshi, Chu, Demers et al., 2020) as well as future trading behaviours (Preis, Moat and Stanley, 2013; Salisu, Ogbonna and Adediran, 2021). Consequently, search volume indexes may serve as a metric for quantifying investors' sentiment on climate change, being able to hypothetically anticipate bubble behaviors.

3. Market Dynamics

This section is devoted to identifying speculative bubbles as well as euphoric moments present in the renewable energy market. As mentioned above different events (i.e. financial bubbles and explosive periods) require different tools.

3.1. Dataset

The dataset utilized in the subsequent analysis will be comprised of two principal categories of factors, economic variables, and search volume indexes. The response variable selected for the study is the global stock index RENIXX (Renewable Energy Industrial Index, ISIN: DE000RENX014), which represents a stock market index designed to monitor the performance of the leading thirty renewable energy companies listed on various international stock exchanges. This index aims to provide investors with insights into the overall performance of the renewable energy market. The remaining explanatory variables are detailed as follows.

- Crude Oil West Texas Intermediate (WTI) Futures, available at the *Investing.com* platform.
- The Morgan Stanley Capital International (MSCI) World Index, an index designed to measure the performance of equity markets at a global level, available at the *Investing.com* platform.
- The Global Economic Uncertainty Policy (EPU) index proposed by Baker, Bloom and Davis (2016).
- The Financial Stress Index (FSI), available at the Office of Financial Research.

Regarding Google Trends, a total of eight search volume indexes have been chosen to measure climate sentiment and interest in green assets. Some of the most common terms associated with both physical risk and transition risk are considered.

- Climate sentiment: *"global warming"*, *"natural disasters"*, *"new technology"*, *"carbon price"*, *"carbon tax"* and *"green energy"*.
- Green assets attention: *"energy index"*, *"energy shares"*.

To ensure uniformity and consistency, the *"Glimpse's Google Trends Chrome Extension"* was utilized to have all indexes in absolute values. The dataset has a total of thirteen variables at a monthly frequency, covering the time span from January 2005 to December 2022.

3.2. Euphoric moments

Following the global financial crisis, there has been a significant interest in the utilization of econometric tests to identify exuberance in asset markets. As a result, numerous new econometric methodologies have been proposed for the purpose of detecting these phenomena. An approach that has gained increasing popularity is the SADF test developed by Phillips et al. (2011), subsequently extended by Phillips et al. (2015a,b) to the Generalized SADF test (GSADF). The primary advantage of employing these methodologies is associated with a recursive estimation of ADF tests on sub-samples of the data. Following the notation proposed in Vasilopoulos, Pavlidis and Martínez-García (2022), these tests have their own foundation on the following regression equation,

$$\Delta y_t = a_{r_1,r_2} + \gamma_{r_1,r_2} y_{t-1} + \sum_{j=1}^{k} \phi^j_{r_1,r_2} \Delta y_{t-j} + \epsilon_t,$$

where y_t denotes the time series, Δy_{t-j} with $j = 1, ..., k$ are lagged first differences of the series, $\epsilon_t \sim \mathcal{N}(0, \sigma^2_{r_1,r_2})$ are the Gaussian residuals, and $a_{r_1,r_2}, \gamma_{r_1,r_2}, \phi^j_{r_1,r_2}$ are regression coefficients. The terms r_1 and r_2 represent the initial and final points of a sub-sample period. The hypothesis setup may be summarised as follows,

$$\begin{cases} H_0 : \gamma_{r_1,r_2} = 0, \\ H_1 : \gamma_{r_1,r_2} > 0, \end{cases}$$

with the test statistics for the null hypothesis given by,

$$ADF_{r_1}^{r_2} = \frac{\hat{\gamma}_{r_1,r_2}}{s.e.(\hat{\gamma}_{r_1,r_2})}. \tag{1}$$

Phillips et al. (2011), revisited the standard ADF, proposing an approach based on a recursive estimation of Eq. 1, and defining the supremum of this sequence by,

$$SADF(r_0) = \sup_{r_2 \in [r_0, 1]} ADF_0^{r_2}.$$

As for the standard ADF, the rejection of the null hypothesis of a unit root necessitates that the SADF statistic surpasses the critical value from its limit distribution in the right tail. Nevertheless, the alternative hypothesis of the SADF test allows the occurrence of explosive dynamics in specific segments of the sample.

Phillips et al. (2015a,b) proposed the generalized SADF (GSADF), which is able to cover a larger number of sub-samples respect the SADF. Setting r_0 as the minimum window size, Eq. 1 is estimated for several possible sub-samples, obtained by changing the boundaries, r_1 and r_2. In the SADF, the start and the end of explosive periods can be obtained with the Backward ADF (BADF) test. A similar strategy based on the sequence of Backward SADF (BSADF) statistics was developed in Phillips et al. (2015a,b),

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} SADF_{r_1}^{r_2}.$$

Letting r_e and r_f be the start and the end of euphoric moments, an estimate can be constructed as follows.

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \{ r_2 : BSADF_{r_2}(r_0) > CI_{r_2}^{\alpha} \},$$
$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e, 1]} \{ r_2 : BSADF_{r_2}(r_0) < CI_{r_2}^{\alpha} \},$$

where $CI_{r_2}^{\alpha}$ is the critical value of the SADF for the $[r_2 T]$ set of observations. Thus, the ADF statistic and its extensions turned out to be reasonable econometric tools to detect explosive behaviours. This is implemented using the `radf` function available in the R package `exuber`. Figure 1 shows the estimated BSADF statistics together with the sequence of 95% critical values for the RENIXX index. The shaded areas indicate periods in which the statistic surpasses its critical value, providing evidence of exuberance from the end of 2019.

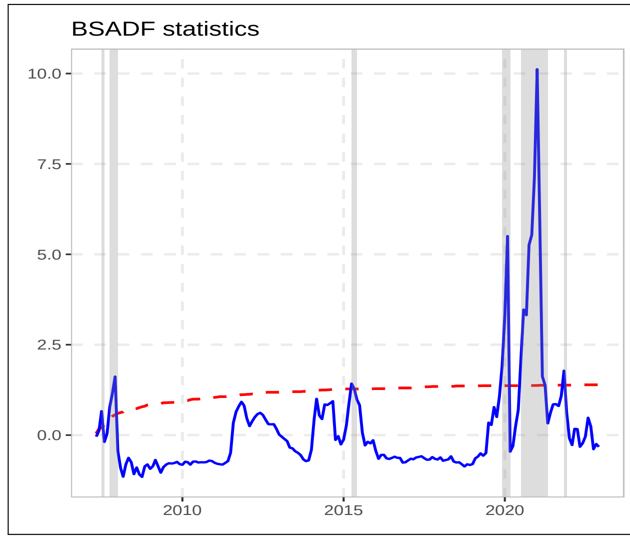

Figure 1: BSADF test with 95% critical values, for the RENIXX index.

3.3. Bubbles

Using the same logic of Boubaker et al. (2022), a change point detection strategy is adopted to determine bubble moments. However, the interest is not to identify only the burst stage but the overall process, i.e. formation, burst, and decline. Enoksen et al. (2020) outlined as price volatility, trading volumes, and the number of transactions are relevant factors to detect bubble stages in the crypto market. In this view, a non-parametric sequential change point model on absolute log-returns of the series is proposed to detect bubble episodes. Formally, a sequence of observations $\{x_1, x_2, ...\}$ is drawn from the series of random variables $\{X_1, X_2, ...\}$ with one or more changes in the distribution at unknown points $\{\tau_1, \tau_2, ..., \tau_m\}$. Assuming that observations are independent and identically distributed (i.i.d.) inside each segment, the distribution of the sequence can be written as follows,

$$X_t \sim \begin{cases} F_0 & if \ t \leq \tau_1, \\ F_1 & if \ \tau_1 < t \leq \tau_2, \\ \vdots & \\ F_{m-1} & if \ \tau_{m-1} < t \leq \tau_m, \end{cases}$$

where F_i represents the distribution in each segment. In this regard, the performance of the statistical test widely depends on the assumptions around F_i. If there is a fixed sample size[1] $\{x_1, x_2, ..., x_T\}$, and a change point at some time τ exists, then observations prior to this point follow the distribution F_0, while the remaining observations follow distribution F_1. Testing for a change in the distribution after k observations leads to the following setup of hypothesis,

$$\begin{cases} H_0 : X_t \sim F_0(x; \theta_0) \quad \forall t, \\ H_1 : X_t \sim \begin{cases} F_0(x; \theta_0), & t = 1, 2, ..., k, \\ F_1(x; \theta_1), & t = k+1, k+2, ..., T, \end{cases} \end{cases}$$

where θ_i represents a vector of unknown parameters of the underlying distribution. This problem can be addressed using a two-sample hypothesis test, which statistic relies

[1] This is also known as Batch change detection scenario. (Ross, 2015).

on the assumed distribution. Non-parametric tests may be employed to avoid such assumptions.

After the selection of a two-sample test statistic $D_{k,T}$ and an appropriate threshold point $h_{k,T}$, it becomes possible to test for a change in the distribution of the process immediately following observation x_k. However, in practice, the change point k is not known in advance, and therefore $D_{k,T}$ needs to be evaluated for every time point $1 < k < T$.

$$D_T = \max_{k=2,\dots,T-1} D_{k,T}, \qquad \hat{\tau} = \arg\max_k D_{k,T},$$

for some threshold h_T. Considering a sequential perspective, the above framework can be extended allowing new observations and the presence of multiple change points. Let x_t be the t^{th} observation for $t \in \{1, 2, \dots\}$. When a new observation x_{t+1} is received the sample $\{x_1, x_2, \dots, x_{t+1}\}$ is treated using a fixed length perspective and D_{t+1} be computed considering the above approach. In this sequential setting, the threshold h_t is typically chosen so that the probability of a type one error remains constant over time. Thus, under the null hypothesis,

$$\begin{aligned} \mathbb{P}(D_1 > h_1) &= \alpha, \\ \mathbb{P}(D_t > h_t \mid D_{t-1} \le h_{t-1}, \dots, D_1 \le h_1) &= \alpha, \quad t > 1. \end{aligned} \tag{2}$$

Generally, the conditional distribution in Eq.2 is intractable, requiring Monte Carlo simulations to compute h_t for a pre-determined level of α. The R package `cpm` developed by Ross (2015) allows to develop such statistical tests. Thus, a sequential change point detection model with the Kolmogorovon-Smirnov statistic (KS-CPM) is proposed to detect bubble stages. Figure 2 shows the number of change points for the absolute log-returns of the RENIXX index[2]. The analysis indicates the existence of two change points, resulting in the identification of three distinct segments. It can be hypothesized that the initial change point marks the end of the Clean-Tech bubble, the second one corresponds to a no-bubble period, and the third one is associated with the starting of a new phase of speculation, referred to as the Climate bubble[3].

The proposed methodology was initially tested against the BSADF using the same setup as proposed in Monschang and Wilfling (2021), demonstrating improvements in terms of bubbles detection. For more details, please refer to the Appendix.

4. Market Drivers

This section serves two objectives. The first aim is to investigate whether the green bubbles within the renewable energy market are similar in nature. While the second aim is to investigate if explosive behaviours can be anticipated.

[2]The model was initialized with a number of observations equal to 20% of the overall sample and an Average Run Length (ARL) to 5000 (Ross, 2015).

[3]Present times are marked by a significant focus on the global challenge posed by climate change. Therefore, the current speculative phase has been referred to as the Climate bubble.

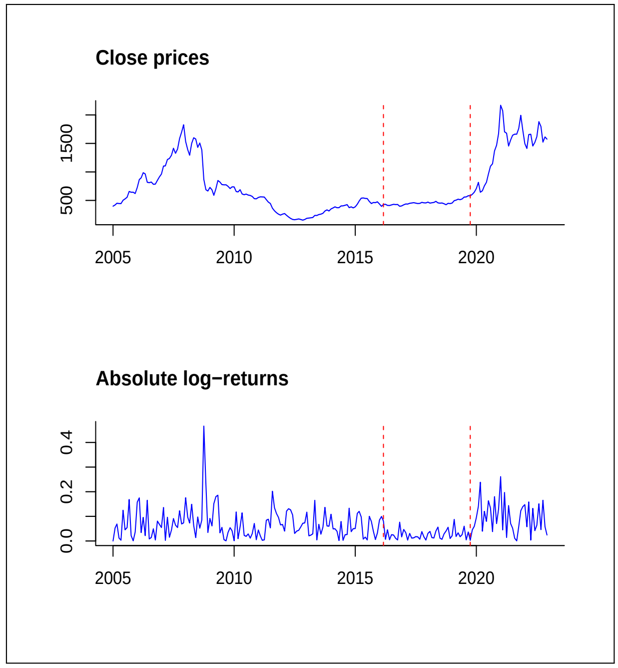

Figure 2: KS-CPM for the RENIXX index.

4.1. Green bubble's paradigm

As discussed by Blanchard and Watson (1982), bubbles are often linked to the outcomes of the invisible hand. Investor optimism and herd mentality are however recognized as possible main drivers of such events. When investors become excessively optimistic about the future of a specific asset, they initiate a vicious cycle of buying, leading to inflated prices. In 2017, Shiller (2017) coined the term of *"Narrative Economics"*, to denote the study of how stories may influence economic outcomes. Shiller's proposition seeks to underscore the significant role of narratives in driving economic behaviour, extending beyond the conventional economic models relying on rationality and efficient markets. In essence, the focus lies in the narrative's capacity to impact individuals' beliefs, and expectations, influencing economic choices. From this perspective, psychological factors, such as the fear of missing out or belief in a new paradigm, may play a relevant role in bubble formation. Thus, the bubble stages recognized in Section 3 are analyzed from a human sentiment perspective.

Figure 3 illustrates the first-lagged series of Google Trends [4] in relation to the three stages of the RENIXX index. The initial speculative period is characterized by a high interest in the advent of new technologies, global warming, and a new energy source, i.e. green energy. This aligns with the findings of Giorgis et al. (2022), which emphasizes as the core narrative of the clean-tech bubble was *"salvation and profits"*.

[4]Google Trends data are expressed in absolute values. To standardize the series, the mean is subtracted, and the results are divided by the deviance. Furthermore, all series are subject to first-order lagging. This means that for the response variable at time t, all covariates are lagged at time $t-1$.

> While clean-tech represented an opportunity to be exploited for profit -an opportunity bigger than the Internet- it also had a quasi-religious dimensions to it: investing in clean tech could promise salvation.
>
> $[\cdots]$
>
> The narratives of alternative clean or renewable technologies of energy, which followed the anti-nuclear narratives of contamination and doom, also powered the clean-tech bubble. Clean and renewable give rise to a spiritual, quasi-religious, or mystical imagery of purification, healing, and renewal, which contrasts with the deeply entrenched and collectively-shared imagery of crisis and pollution that nuclear energy and fossil fuels invoke.

Figure 3 shows how the interest in green energies persists even during the Climate bubble. However, the focus on new technologies and global warming has shifted towards a fear of an increasing carbon price. Additionally, speculation activities, as evidenced by the search volume of the terms *"energy index"* and *"energy shares"*, are higher compared to past values. Perhaps the paradigm proposed by Giorgis et al. (2022) requires reconfirmation or even amplification. Following the Paris Agreement, there has been a noticeable interest in climate change across almost all developed nations. This growing interest was like a spring that has been steadily charged over the past years, which is now ready to burst; accentuating the *"profit"* dimension of the paradigm. Conversely, the growing interest in green policies indicates how individuals started to be frightened by a compulsive dependence on fossil fuels. This together with a constant interest in green energies may amplify the quasi-religion concept of *"salvation"*. With these enhancements, there is the potential to generate those virtuous cycles that were missing during the Clean-Tech bubble, establishing new bases for the ecological transition.

4.2. Causes of exuberant movements

Euphoric moments are characterized by brief periods of exuberance. These explosive moments are obtained by converting the RENIXX index into a binary variable on the results of the BSADF test. This new variable will take the value of one when an explosive moment is present and zero otherwise.

In previous research (Agosto and Cafferata, 2020; Su, Qin, Chang and Ţăran, 2023), the logit model was used to investigate the existence of potential drivers. In the present work, the elastic net regularization technique is proposed to improve model performance. This extension allows an automatic feature selection while simultaneously addressing multicollinearity issues. The elastic-net regularization has the aim to balance the trade-off between l_1 and l_2 penalties, increasing model stability. The proposed model, which is an elastic-net regularized logistic regression model, is implemented using the R package `caret`. Let's assume there are $K = 2$ classes (i.e. binary variable), a sample size of length N, and a response variable $\{y_i\}_{i=1}^N$. If a number of p features denoted by $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{ip})$ for all observations is present, the probabilities of $\{y_i\}_{i=1}^N$ belonging to the interest class can be estimated. For the logistic regression, the probabilities are modelled using the sigmoid function,

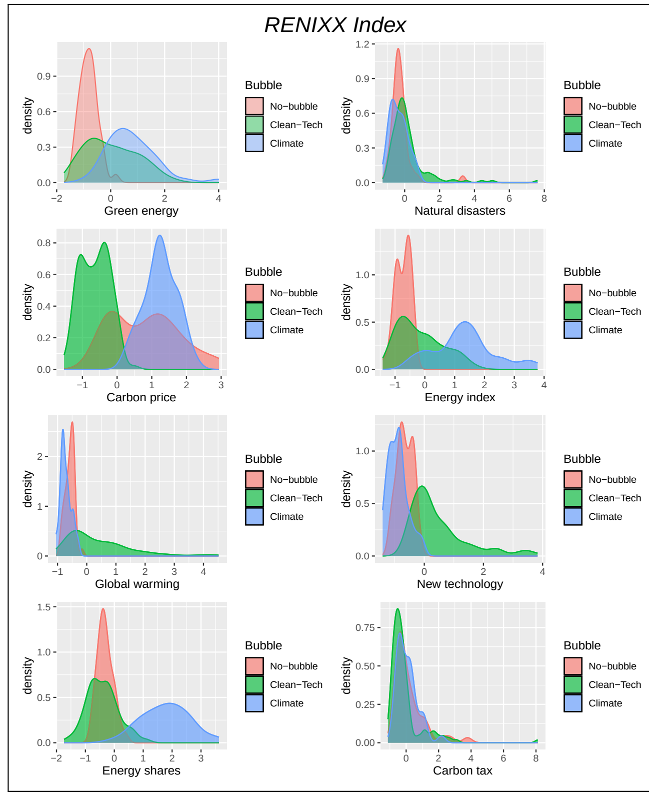

Figure 3: First lagged series of Goggle Trends with respect to the RENIXX index.

$$p_i = \mathbb{P}(y_i = 1 \mid \mathbf{x}_i) = \frac{1}{1 + \exp[-(\beta_0 + \mathbf{x}_i\beta)]}, \qquad \forall i,$$

where β is a column vector of length p. In this setup, the elastic-net regularization is included in the model by a modification of the objective function,

$$\min_{\beta_0,\beta} \left\{ -\frac{1}{2N} \sum_{i=1}^{N} [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)] + \lambda\Omega \right\},$$

$$\Omega = \left[\alpha\|\beta\|_1 + \frac{1}{2}(1 - \alpha)\|\beta\|_2^2 \right],$$

where λ is the regularization parameter, while $\|\beta\|_1$ is the l_1-norm, α is the mixing parameter, and $\|\beta\|_2$ is the l_2-norm. A critical step is the estimate of λ and α, which are typically chosen by cross-validation. Due to the temporal nature of time series data, performing cross-validation requires special considerations. An expanding window cross-validation technique [5] is, therefore, adopted for tuning both λ and α.

[5] The expanding window cross-validation was performed considering an initial set of 135 observations and a window size of 20.

Variable	Coefficient
Energy index	0.289
Energy shares	0.538
Natural disasters	-0.059
New Technology	-0.035
Carbon tax	-0.099
Δ_{RENX}	0.481
Δ_{MSCI}	0.147
Δ_{Oil}	0.113
Δ_{EPU}	-0.035
Time	0.197

Table 1
Results of the elastic-net regularization procedure.

The feature set comprises the first lagged series of both economic variables and Google Trends. To enhance model stability, search volume indexes are standardized, while financial time series are first differentiated before applying standardization[6]. Additionally, a new variable namely Δ_{RENX} was created to measure the discrepancy between what happened in the real market and what was searched online. Put differently, Δ_{RENX} is the difference between the RENIXX index and the volumes of the word *"energy index"* at the time before. Model performance is evaluated by splitting the data into training and test set [7]. Table 1 shows the results of the elastic-net regularization procedure. A remarkable positive impact is provided by Δ_{RENX}, and by the search volume of the terms *"energy share"* and *"energy index"*. The accuracy of the estimated model on the test set is equal to 88%, which is outlined in Table 2.

The proposed elastic-net regularized logistic regression model is then compared to the conventional logit model. With the same splitting framework, the logit model is built using a Backwards Stepwise Selection (BSS) procedure. The likelihood-ratio test is utilized to compare various nested models[8]; while Pregibon's link test and the Variance Inflation Factor (VIF) are adopted to assess the model's validity. The estimated logit model is composed of four variables, Δ_{RENX}, Δ_{MSCI}, and the search volume of the terms *"new technology"* and *"energy index"*. With an accuracy of 64% in the test set, Table 3 displays the confusion matrix of the logit model. Compared to the simpler alternative, the elastic-net regularized logistic regression model exhibits significantly superior out-of-sample forecasting performance. Should be however noted that the outcomes depend highly on the strategy employed to identify exuberant periods. Nevertheless, both models outline the importance of human sentiment in anticipating future moments of exuberance in the renewable energy sector. This is in line with the *"Narrative Economics"* idea developed by (Shiller, 2017),

N=25	Reference	
Prediction	0	1
0	17	3
1	0	5

Table 2
Confusion matrix for the out-of-sample forecasting, elastic-net regularized logistic regression model.

N=25	Reference	
Prediction	0	1
0	8	0
1	9	8

Table 3
Confusion matrix for the out-of-sample forecasting, logit model.

which emphasizes the role of collective beliefs and emotions in influencing financial outcomes. Therefore, policymakers should incorporate the dynamics of psychological and sociological factors into their strategies, transcending conventional economic models.

5. Financial stability

This section is devoted to investigating possible propagation effects on the stability of the financial system. Additionally, some econometric models are proposed to forecast future market values of the RENIXX index. Then, the section concludes by providing relevant policy implications.

5.1. Success is failure

Minsky postulated that within a capitalist economic framework, the emergence of business cycles is a natural outcome (Minsky, 1986). In this view, the economic system and the financial market are strictly connected. As illustrated in Minsky (1992),

> A part of the financing of the economy can be structured as dated payment commitments in which banks are the central player. The money flows are first from depositors to banks and from banks to firms: then, at some later dates, from firms to banks and from banks to their depositors.
>
> [· · ·]
>
> Thus, in a capitalist economy the past, the present, and the future are linked not only by capital assets and labor force characteristics but also by financial relations.

From this perspective, not only a rapid rise of green stocks beyond their book value but also a rapid shift towards a low-carbon economy could affect financial stability, triggering a *"Climate Misnky"* moment. This is what Carney (2016) referred to as the second climate paradox, i.e. *"success is failure"*.

[6]This further transformation improved drastically model performance. Moreover, possible deterministic trends were included in the analysis using a time variable.

[7]The test set is composed of the last twenty-five observations. The choice of this splitting setup was based on the limited number of explosive phenomena, twenty-six.

[8]The threshold to reject the null hypothesis was fixed to 5%.

Variable	ADF	KPSS
RENIXX index	✓	✓
MSCI	✓	✓
FSI	✓	✓
EPU	✓	✓
Oil price	✓	✓
Energy index	✓	✓
Energy shares	✓	✓
Green energy	✓	✓
Global warming	✓	✓
Natural disasters	✓	✓
New Technology	✓	✓
Carbon price	✓	✓
Carbon Tax	✓	✓

Table 4
Stationarity tests considering a critical value of 5%.

Granger causality test, FSI	
Variable	P-value
RENIXX index	0.052*
Oil price	0.029**
Granger causality test, RENIXX index	
Variable	P-value
FSI	0.435
Oil price	0.018**
Granger causality test, oil price	
Variable	P-value
RENIXX index	0.747
FSI	0.052*

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 5
Granger causality tests, *"Climate Minsky"* moments.

The presence of such a risk is examined within an econometric framework, wherein all variables are transformed into their logarithmic representation, followed by the application of first difference operation [9]. Table 4 shows the results of both the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS), showing that all series are $I(1)$ for a critical value of 5%. Table 5 presents the results of the Granger causality test[10], as developed by Granger (1969). The test explores the causal relationship between the FSI and two variables thought to be potential drivers of *"Climate Minsky"* moments, i.e. the RENIXX index and the oil price. The results show the existence of causality among the considered variables. Hence, a Vector Autoregressive (VAR) model is adopted to investigate how past values of the RENIXX index and the oil price may affect future financial stability conditions. Formally, a VAR consists of a set of K endogenous variables $\mathbf{y}_t = (y_{1t}, y_{2t}, ..., y_{Kt})$ for $k = 1, ..., K$. The VAR(p)-process is therefore defined as,

$$\mathbf{y}_t = A_1\mathbf{y}_{t-1} +, ..., + A_p\mathbf{y}_{t-p} + \mathbf{u}_t, \tag{3}$$

where A_i are $K \times K$ coefficient matrices for $i = 1, 2, ..., p$, and $\mathbf{u}_t$ is a k-dimensional vector with $\mathbb{E}(\mathbf{u}_t) = 0$ and time-invariant positive definite covariance matrix $\mathbb{E}(\mathbf{u}_t\mathbf{u}_t^T) = \Sigma_\mathbf{u}$. Additional dummy variables are included to account for potential seasonality patterns. The `varselect` function available in the R package `vars` is adopted to select the lag order of the model[11]. Table 6 shows the results of the estimated VAR(1) model for the equation regarding the FSI. The results indicate a significant causality between the RENIXX index at the preceding date and the FSI, while the coefficient of the first-lag oil price is not statistically significant. Figure 4 shows the impulse response function from a one-standard-deviation negative shock in the RENIXX index.

A positive coefficient in the VAR(1) model indicates a positive linear relationship between the RENIXX index and the FSI, which means that past values of the predictor variable have a positive impact on the current value of the response variable. On the other hand, the impulse response function underlines an inverse effect immediately following a shock. Put differently, there is a short-term negative deviation from the expected positive relationship between the variables. As the system stabilizes, the long-term positive relationship reasserts itself.

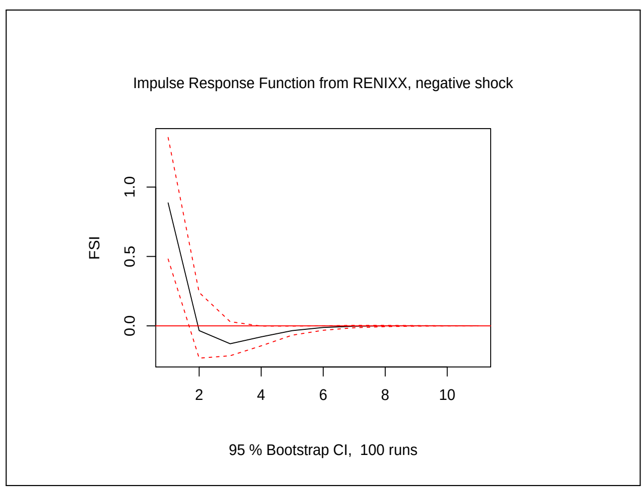

Figure 4: Impulse response function of FSI from a negative shock in the RENIXX index.

The findings are consistent with speculative patterns. When a bubble forms, there is a gradual increase in pressure on the financial system, peaking at the bubble's burst. This leads to a drastic down in asset returns, affecting financial stability and with the potential to trigger a Minsky moment. However, as the system stabilizes, the possibility of a Minsky moment gradually disappears. When examining the response to a specific shock, the standard impulse response

[9] The logarithm transformation was used to make the variance of the variables stationary. While the first difference operation aimed at achieving stationarity in the mean. The logarithm transformation was not applied to the FSI due to the presence of some zeros. In turn, the Breusch-Pagan test was conducted, and it did not reveal any evidence of heteroskedasticity in the time series of first differences.

[10] The data are on a monthly basis and therefore the Granger causality test was performed considering a lag order of twelve.

[11] The Akaike's Final Prediction Error (FPE) criterion was the criteria chosen to select the optimum lag order of the models.

VAR(1)				
Variable	Estimate	Std. Error	t value	Pr(>|t|)
Renixx.l1	4.079	1.412	2.890	$< 0.01^{***}$
FSI.l1	0.366	0.083	4.440	$< 0.01^{***}$
Oil_p.l1	0.346	1.058	0.330	0.744
sd1	-0.272	0.511	-0.530	0.596
sd2	0.128	0.507	0.250	0.801
sd3	0.576	0.507	1.140	0.257
sd4	-0.546	0.512	-1.070	0.288
sd5	0.006	0.506	0.010	0.990
sd6	0.212	0.510	0.420	0.679
sd7	-0.137	0.508	-0.270	0.789
sd8	0.362	0.505	0.720	0.474
sd9	0.345	0.505	0.680	0.495
sd10	0.577	0.506	1.140	0.256
sd11	-0.111	0.508	-0.220	0.827
Multiple R-Squared: 0.136				

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 6
VAR model, results of the equation related to FSI.

function makes the assumption that all other variables in the system remain constant. While this is a commonly used approach, it may be too restrictive in practice. Additionally, it is essential to extend the VAR(1) model to properly satisfy validation tests, such as the multivariate Portmanteau test for autocorrelation, the multivariate ARCH test for heteroskedasticity, and the multivariate Jarque-Bera test for normality Pfaff (2008). Therefore, further developments are necessary to have more robust results. Nevertheless, the current analysis has provided valuable insights into the financial consequences of a sudden and unexpected negative shock in the renewable energy sector. In contrast, similar evidence is not found for the oil price, which has an insignificant coefficient.

5.2. Forecasting

Based on previous findings, future trends of the RENIXX index may be crucial in preserving financial stability in the transition process. The year 2015 marks a significant turning point in global interest regarding climate change. During this year, several significant events and developments contributed to a remarkable growth in public awareness to address the global challenge posed by climate change. Some of the key events include:

- Clean Energy Investment Forum in Canada (January 2015),
- United Nations Sustainable Development Goals (September 2015),
- Paris Agreement (December 2015).

Therefore, the following analysis is performed considering only observations after January 2015. Table 7 presents the results of the Granger causality test for variables that were found to be significant for the RENIXX index. The findings indicate a unidirectional Granger causality running from

Granger causality test, RENIXX index	
Variable	P-value
FSI	0.136
MSCI	0.377
EPU	0.361
Oil price	0.045^{**}
Energy index	0.081^{*}
Energy shares	$<0.01^{***}$
Green energy	0.715
Global warming	0.567
Natural disasters	0.995
New Technology	0.942
Carbon price	0.298
Carbon Tax	0.170
Granger causality test, oil price	
Variable	P-value
RENIXX index	0.845
Energy shares	0.766
Energy index	0.673
Granger causality test, energy index	
Variable	P-value
RENIXX index	0.244
Energy shares	0.334
Oil price	0.290
Granger causality test, energy shares	
Variable	P-value
RENIXX index	0.106
Energy index	0.206
Oil price	0.298

Table 7
Granger causality tests, among the RENIXX index and the covariates.

the oil price and the search volumes of the terms *"energy shares"* and *"energy index"* to the RENIXX index. Three different models are developed and compared to increase forecasting accuracy [12]. The initial and most straightforward model is the SARIMA(p,d,q)×(P,D,Q)s model[13].

$$\phi(L)(1-L)^d \Phi(L^s)(1-L^s)^D y_t = \theta(L)\Theta(L^s)\epsilon_t, \quad (4)$$

with,

$$\phi(L)y_t = \left(1-\phi_1 L^1 - \phi_2 L^2 -, ..., -\phi_p L^p\right) y_t,$$
$$\theta(L)\epsilon_t = \left(1+\theta_1 L^1 + \theta_2 L^2 +, ..., +\theta_q L^q\right) \epsilon_t,$$
$$\Phi(L^s)y_t = \left(1-\Phi_1 L^{1s} - \Phi_2 L^{2s} -, ..., -\Phi_P L^{Ps}\right) y_t,$$
$$\Theta(L^s)\epsilon_t = \left(1+\Theta_1 L^{1s} + \Theta_2 L^{2s} +, ..., +\Theta_Q L^{Qs}\right) \epsilon_t,$$

where L is the lag operator, y_t is the time series at time t, and ϵ_t the error term at time t. Using the function `auto.arima` provided by the R package `forecast` the estimated model results in an ARIMA(1,1,1). Exogenous variables may be included in Eq. 4, considering a SARIMAX(p,d,q)×(P,D,Q)s model,

$$\phi(L)(1-L)^d \Phi(L^s)(1-L^s)^D y_t = \theta(L)\Theta(L^s)\epsilon_t + \mathbf{X}_t\beta,$$

[12] All proposed models were developed on log-transformed series.
[13] The SARIMA(p,d,q)×(P,D,Q)s model was considered as the baseline model, and no additional extensions were developed.

Model	MAPE	RMSE
ARIMA	0.954%	0.089
ARIMAX-EGARCH	0.409%	0.040
VECM	0.502%	0.041

Table 8
Forecasting accuracy for all proposed models, RMSE and MAPE.

where $\mathbf{X}_t$ is the vector of exogenous variables at time t. With the same approach, the estimated model turned out to be an ARIMAX(1,0,1) model. To treat possible asymmetric effects in the conditional variance, the model is further extended by including an EGARCH(1,1) model (Nelson, 1991). Formally, let ϵ_t be the residual from the mean process at time t,

$$\epsilon_t = \sigma_t z_t$$
$$\log(\sigma_t^2) = \omega + \beta g\left(z_{t-1}\right) + \alpha \log(\sigma_{t-1}^2),$$

where $g\left(z_t\right) = \theta z_t + \lambda\left(\left|z_t\right| - \mathbb{E}\left[\left|z_t\right|\right]\right), \sigma_t^2$ is the conditional variance, $\omega, \beta, \alpha, \theta$ and λ are coefficients to be estimated. For its ability to model asset returns, the hyperbolic distribution is assumed for the variable z_t (Jaschke, 1997). Consequently, the model takes the form of a combined ARIMAX(1,0,1)-EGARCH(1,1) model, where the ARIMA component deals with the conditional mean of the time series, and the GARCH part deals with the conditional variance.

Finally, a VAR model is developed to capture the potential endogenous nature of the variables. The Johansen procedure (Johansen, 1991) is further employed to test for the existence of cointegration and the suitability of a Vector Error Correction Model (VECM). Formally, Eq. 3 is extended allowing for long-run relationships,

$$\Delta \mathbf{y}_t = \alpha\beta^T \mathbf{y}_{t-p} + \Gamma_1 \Delta \mathbf{y}_{t-1} +, ..., +\Gamma_{p-1} \mathbf{y}_{t-p+1} + \mathbf{u}_t,$$
$$\Gamma_i = -(I - A_1 -, ..., -A_i), \quad i = 1, ..., p-1$$
$$\alpha\beta^T = -(I - A_1 -, ..., -A_p).$$

Using the same approach proposed by (Pfaff, 2008), a VECM with a lag-order of four and one cointegration term is estimated[14]. The comparison of all proposed models is conducted based on their performance using future values of the RENIXX index up until the month of July 2023. The findings are outlined in Table 8, which shows the accuracy of the three models in terms of MAPE and RMSE. The ARIMA model exhibits the poorest performance, whereas the VECM and the ARIMAX-EGARCH model provide similar results. Given the higher complexity of the VECM, an exogenous structure should be preferred.

The analysis outlines the importance of incorporating economic variables like oil price and search volume indexes to forecast future values of the RENIXX index.

[14] A critical value of 5% was used to select the order of the cointegrating relationships.

5.3. A Schumpeterian perspective

While certain bubbles may be viewed from a social hypothesis perspective, there is unequivocal evidence that the present time is characterized by a significant interest in green investing. As outlined in Section 3 this could be a new attempt at the ecological transition. Indeed, climate sentiment is essential to pursue sustainable and ecological behaviours. Indeed, low levels of attitudes towards climate issues may undermine all efforts to effectively tackle the global challenge posed by climate change. At the same time, investors' overestimates should be limited to avoid potential *"Climate Minsky"* moments.

During the realization of the *"Financial Instability Hypothesis"*, Hyman Minsky was widely influenced by Joseph Schumpeter's ideas on business cycles, and the role of the entrepreneur in economic developments. In this view, what is going on has many similarities with the Railway Mania at the end of the 19^{th} century. From Schumpeter's view, railroadization was fueled by technological innovation in the form of steam-powered locomotives and railways. Due to the potential economic benefits, this new technology attracted several investors, leading to a boom in railway investments and disrupting existing transportation methods. Schumpeter coined the term *"creative destruction"* to describe this transformation process, in which old technologies are gradually replaced by new ones. However, the transition did not come without a cost. After the peak of Railway Mania, a bust followed, leading to a significant economic recession. Many railway projects failed, and numerous investors suffered losses. These cycles of boom and bust were named by Schumpeter the *"gales of creative destruction"*.

The history of the Railway Mania is a real example of how periods of rapid technological growth and speculative investments can lead to both great innovations and subsequent economic downturns. Similarly, green bubbles may be seen as a *"necessary evil"* for the success of the green transition. The adoption of efficient environmental technologies and the reduction of environmental impact can be considered innovative activities that create new markets as well as new forms of competition. Then, green bubbles would be the way in which the financial market responds to the idea that environmental sustainability represents a new economic frontier, and therefore profits from it through speculative transactions. In this sense, green bubbles can be seen as a side effect of technological innovations, a source of economic instability resulting from an attempt at ecological transition.

In light of this, policy-makers should proactively integrate into their strategies the potential consequences of a weakening of the *"salvation and profit"* paradigm. By doing so, they may address the challenges associated with green bubbles, ensuring a more resilient financial system during this crucial phase of ecological transition.

5.4. Limitations of the analysis

The current study was conducted from an econometric perspective and presents the following limitations. Firstly, the test developed to detect bubble behaviours is limited to changes in the process's variability. The methodology may be improved by undertaking a conjoint analysis that incorporates additional factors, such as asset transition volumes. Secondly, the analysis was widely based on Google Trends, which provides insights into popular topics but may not be as comprehensive as data from official journals. Thus, a more extensive textual analysis is needed to have a comprehensive view of the role played by the *"Narrative economy"* on green asset prices. Thirdly, all proposed models were based on the constant coefficient assumption, which may not always hold in reality. To address this limitation, a Bayesian framework should be implemented in future works. By overcoming these drawbacks, policymakers would gain access to a more robust framework for assessing potential financial instability arising from green bubbles.

6. Conclusions

The emergence of green bubbles is a recent phenomenon. While they share some common characteristics with speculative activities, their underlying drivers are linked to environmentally sustainable and socially responsible investments. Consequently, it might be appropriate to consider them within the framework of a social bubble hypothesis. However, the likelihood of a *"Climate Minsky"* moment should not be dismissed. This article aimed to investigate the bubbles within the renewable energy sector and their effects on the stability of the financial system.

In Section 3, a distinction between euphoric behaviours and the bubble process was outlined, with the introduction of alternative methods for their detection. The analysis revealed the existence of explosive moments and identified two distinct bubble stages. Moving on to Section 4, bubbles are revisited under a *"Narrative economics"* lent (Shiller, 2017). The analysis utilized pre-established climate change-related volume search indexes and found evidence supporting the *"salvation and profits"* paradigm proposed by Giorgis et al. (2022). An elastic-net regularized logistic regression model was then developed to anticipate future euphoric behaviours. In essence, Section 4 emphasized the significance of social narratives in influencing market dynamics within the renewable energy sector.

In Section 5, an econometric framework was used to investigate the potential occurrence of *"Climate Minsky"* moments, either triggered by a shift in the oil price or an increasing interest in the renewable energy sector. The study revealed that changes in the oil prices did not significantly affect the stability of the financial system; while notable propagation effects were observed for the RENIXX index. As a result, further investigations were conducted to forecast future market values, leading to the discovery of a unidirectional causality between the RENIXX index, oil price, and search volume of the terms *"energy shares"* and *"energy index"*. As the literature on *"Climate Minsky"* moments is in its early stages, future studies should investigate individual clean energy stocks and green assets that could pose risks to financial stability. Moreover, it is crucial to gain a deeper understanding of the possible mechanisms through which changes in asset returns might impact the overall financial system.

While Schumpeter discussed various economic phenomena, including business cycles and the role of innovation in economic development (Schumpeter, 2013), he did not directly focus on speculative bubbles in his writings. However, Schumpeter's view is that entrepreneurs are capital creators but at the same time economic subjects who disturb the equilibrium. From this perspective, green bubbles are both a source of instability and a necessary catalyst to boost the ecological transition. Policymakers and financial authorities must therefore collaborate to promote awareness of climate change, while simultaneously mitigating possible recessions caused by the transition itself.

Appendix

In order to test the KS-CPM outlined in Section 3, a modified version of the data generating process presented in Phillips and Shi (2018) is used. Formally,

$$y_t = \begin{cases} a \cdot T^{-\eta} + y_{t-1} + \epsilon_t, & t \in N_0 \cup N_1, \\ \delta_T y_{t-1} + \epsilon_t, & t \in B, \\ \gamma_T y_{t-1} + \epsilon_t, & t \in C, \end{cases}$$

where $\epsilon_t \sim$ EGARCH(1,1), $\delta_T = 1 + c_1 T^{-\alpha}$, and $\gamma_T = 1 - c_2 T^{-\beta}$. This configuration facilitates the incorporation of

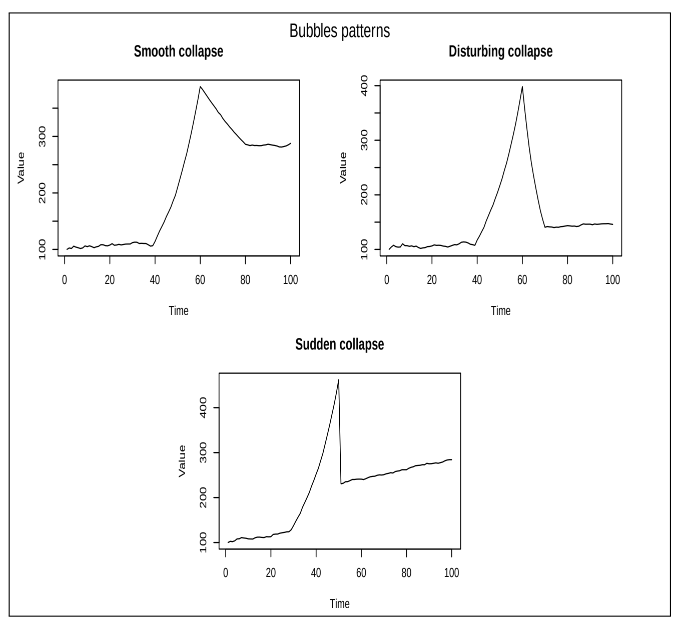

Figure 5: Bubble collapse patterns, simulation example.

leverage effects (Su, 2010), which are observed in financial variables. The set B cover the period in which the bubble inflates, the set C represents the period of bubble collapse, and the set $N_0 \cup N_1$ denotes the no-bubble periods situated at the beginning and end of the sample, respectively.

Pattern	BSADF	KS-CPM
Disturbing	849	962
Sudden	855	931
Smooth	848	895

Table 9
Number of times a single bubble is correctly identified, one thousand Monte Carlo simulations.

Additionally, $y_0 = 100$, $a = c_1 = c_2 = 1$, while the parameters $\alpha, \beta, \eta, B, C$ vary to consider three alternatives collapse patterns (Figure 5). In this context, a comparison is made between the KS-CPM and the BSADF test. One thousand Monte Carlo simulations are conducted for each collapse pattern, and the results are presented in Table 9. Model accuracy is assessed by considering the frequency with the proposed methodologies correctly identifying an individual bubble in the sample. Additionally, the KS-CPM exhibits superior performance also in identifying the start and end dates of the bubble period.

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