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Does every cloud (bubble) have a silver lining? An investigation of ESG financial markets

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ABSTRACT

This paper investigates the presence of financial bubbles in the environmentally friendly investments captured by the ESG markets. By using the log-periodic power law singularity framework, we identified several periods of positive and negative bubbles in the short, medium, and long term. Moreover, we examined the relationship between ESG attention sentiment and financial bubbles. We found an asymmetric effect of ESG sentiment on financial bubbles, i.e., increasing positive and decreasing negative bubbles. Our empirical results provide valuable insights into the stability of environmentally friendly markets, which help risk managers and policymakers respond appropriately to financial and social bubbles.

1. Introduction

The financial world constantly evolves, and new trends, opportunities, and investment products arise. According to PWC (2022) report, global sustainable investment assets will reach US$33.9 trillion in 2026, from US$18.4 trillion in 2021. In recent years, interest in environmental, social, and governance (ESG) investing has grown as investors have become more aware of their investments' impact on society, particularly the environment. Moreover, ESG investing has also gained popularity among institutional investors, with many pension funds and endowments incorporating ESG factors into their investment strategies (Kumar et al., 2020; Alda, 2021; Miglietta et al., 2022; Dmuchowski et al., 2023).

However, while the growth of the ESG market is encouraging, it has led to concerns about a possible financial bubble in this market. The rapid growth of environmentally friendly markets has led some analysts and financial institutions to wonder whether the market is overheating and whether there is a risk of a financial bubble (BIS, 2021). In fact, there is a possibility that risk that investors are rushing into this market without fully understanding the risks and opportunities involved due to good financial performance (Chen and Lin, 2022; Cepni et al., 2023). Hence, there is a risk that investors buy ESG investments based on hype and media coverage rather than careful analysis of the underlying fundamentals of the companies in which they invest.

The vast amount of current academic research on ESG has focused on several strands. Some authors have investigated ESG from the perspective of risk spillovers (e.g., Umar et al., 2021; Chen and Lin, 2022; Khalfaoui et al., 2022; Cepni et al., 2023), other researchers investigated the role of ESG in the banking context (e.g., Birindelli et al., 2018; Brogi and Lagasio, 2019; Paltrinieri et al., 2020; Di Tommaso and Thornton, 2020; Murè et al., 2021; Hummel et al., 2021; Iannuzzi et al., 2023), and other papers have focused on portfolio and stock return analysis (e.g., Friede et al., 2015; Auer and Schuhmacher, 2016; Giese et al., 2019; Billio et al., 2021; Wong and Zhang, 2022; Pacelli et al., 2023; Demiralay et al., 2023).

However, to our knowledge, no study has investigated the ESG market from a financial and social bubbles perspective. As a new investment market presents new trends and risk characteristics, it is important to address the risk situation of financial bubbles in ESG equity investments and how these can be dictated by investor/social sentiment. The increasing search for yield in these financial markets could be due more to the herd effect combined with the "attention-grabbing" hypothesis (Barber and Odean, 2008) than the sustainable investment perspective.

Motivated by the above concerns, our research attempts to fill this gap. The pivotal idea of this work is to discover the existence of financial bubbles in the ESG market. For this purpose, the log-periodic power

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law singularity (LPPLS) model is applied. Thanks to this approach, we can identify positive and negative bubbles (crash) at different time scales, namely short-, medium-, and long-term (like Demirer et al., 2019). As well highlighted by Van Eyden et al. (2023), the LPPLS model is one of the most efficient methods to detect financial bubbles. Indeed, it is important to note that identifying positive and negative multiscale bubbles cannot be effectively addressed through various econometric models, such as the change-point method (Boubaker et al., 2022), bubble detection in real-time (Phillips et al., 2015), or regime-switching model (Nneji et al., 2013). This limitation underscores the significance of the methodology we have employed. This distinction is crucial as it enables the assessment of potential asymmetric effects of investor sentiment on ESG stock market bubbles. Understanding the dynamics of crash and recovery across different horizons can provide important information for market participants. Second, we verify the so-called "social bubble hypotheses" in the financial context. Once we have identified positive and negative bubbles on different time scales, we examine the relationship between ESG attention sentiment and financial bubbles by computing a panel regression model. The results provide valuable insights into the stability of financial ESG markets, which help risk managers and policymakers respond appropriately to financial bubbles. Overall, the empirical findings show several collapses and booms in equity ESG markets from September 2010 to March 2023. The LPPLS outcomes show how positive and negative bubbles are driven mainly by climate change events, such as the Paris Agreement (2015), the United Nations conferences on climate change, the IPCC reports, and the National Climate Assessment reports. Further, we find an asymmetric effect of ESG sentiment on financial bubbles, i.e., increasing positive bubbles and decreasing negative bubbles.

The paper contributes to the literature in several ways. First, we are the first to analyse bubbles in the ESG financial market. In the literature, we can find several papers studying the presence of bubbles in generic financial markets (Zhang et al., 2016; Demirer et al., 2019; Van Eyden et al., 2023), cryptocurrency markets (Bouri et al., 2019; Enoksen et al., 2020; Huber and Sornette, 2022), or green financial markets (Lehnert, 2022; Ghosh et al., 2022). Therefore, our research offers a starting point in this specific context. Moreover, our study contributes to the behavioural finance literature evidencing how sentiment is a key determinant factor of market performance and financial bubbles (e.g., Schmeling, 2009; Zouaoui et al., 2011; Dimpfl and Jank, 2016; Pan, 2020; Van Eyden et al., 2023). However, unlike the existing literature, our focal point is investor sentiment about the ESG market. Indeed, this is the first paper to investigate the effect of ESG sentiment on financial bubbles (positive and negative) at different time horizons.

The following describes the organization of the rest of the article. Section 2 shows the theoretical background of the paper, Section 3 illustrates our data and the methodology, while Sections 4 and 5 show the analysis, the empirical findings and the discussion about results. Finally, Section 6 offers some concluding remarks.

2. Theoretical analysis and hypothesis

The integration of Environmental, Social, and Governance (ESG) principles within financial markets has garnered significant momentum, particularly regarding the impact of media-based ESG sentiment on financial market performance. Research, such as the study by Bofinger et al. (2022), suggests that investors may assign a higher valuation to a company based on its commitment to Corporate Social Responsibility (CSR). As a result, investors are increasingly incorporating a company's ESG stance into their portfolio asset selection, recognizing a potential correlation between high stock returns and effective ESG management (Chen and Lin, 2022; Pacelli et al., 2023). This belief stems from the notion that companies that effectively address ESG concerns tend to enhance their market positions through sustainable decision-making, thereby securing favourable market standing (La Torre et al., 2020; Horn, 2023; Edmans, 2023). Empirical evidence from Aureli et al. (2020) further supports the relevance of ESG disclosure on a company's market value. This study reinforces the argument that companies with high ESG ratings exhibit superior performance during periods of market stress, as observed by Broadstock et al. (2021), who documented better performance among high ESG-rated companies during the COVID-19 pandemic in China. These results are confirmed by Lu et al. (2024), which find how high firms with high levels of CSR experienced moderate stock gains while low CSR companies suffered significant losses during the COVID-19 outbreak. Further, Giese et al. (2019), based on MSCI ESG data, found that ESG information positively influences a company's valuation and overall performance.

The inception and integration of ESG ratings into investment strategies have garnered attention, both from individual and institutional investors alike, reshaping traditional investment paradigms and approaches. However, this swift growth has sparked apprehensions about a potential financial bubble within the ESG market (Edmans, 2023), raising concerns about whether investors comprehend the associated risks and opportunities thoroughly or are simply enticed by its favourable financial performance and heightened media coverage (BIS, 2021; Cepni et al., 2023). For example, Hartzmark and Sussman (2019) shed light on the impact of Morningstar's sustainability ratings. Their results show that funds classified with low sustainability witness net outflows, whereas those classified as high sustainability attract even more significant net inflows. This discernible shift in investor behaviour suggests that the appreciation of sustainability by both retail and institutional investors leads portfolio managers to invest in line with their client's preferences. These findings underline a transformative effect on conventional investment criteria and behaviours due to sustainable investments, potentially fostering pricing inefficiencies (Naeem et al., 2023; Starks et al., 2023). Mynhardt et al. (2017) examined the persistence of several Environmental and Socially Responsible Indexes (SRI) and their traditional equivalents with R/S analysis. The authors find that SRI indices generally show lower efficiency than traditional ones.

As evidenced by theory (Shleifer and Summers, 1990; De Long et al., 1990), the stock markets contain noisy traders subject to behavioural biases that create valuation errors. This undermines the efficient market hypothesis (EMH). This theory assumes that markets readily assimilate all available information into asset prices, making them efficient. However, behavioural finance theories challenge this notion, emphasizing human biases, sentiment, and irrational decision-making in shaping market dynamics. As evidenced in the literature, in the context of ESG investing, these behavioural imperfections are uniquely manifested as sustainability-conscious investors exhibit distinct motivations, divergent tendencies, and different risk characteristics (Rau and Yu, 2023), potentially causing inefficiency in pricing (Bofinger et al., 2022; Billio et al., 2021). Therefore, we hypothesize an existing financial bubble on ESG markets, which leads to our first testable prediction:

- $\mathbf{H}_1$: *The ESG market exhibits financial bubbles*

Furthermore, growing public awareness of sustainability issues can influence investor perceptions of a firm's sustainability value. This awareness has been shown to affect stock prices (Strycharz et al., 2018; Wong and Zhang, 2022; Santi, 2023). Serafeim (2020) provides compelling evidence that public sentiment towards a company's sustainability initiatives directly impacts its valuation. Similarly, Umar and Gubareva (2021) and Akhtaruzzaman et al. (2022) highlight the role of media coverage in facilitating contagion transmission in the context of ESG investments. Moreover, according to Bofinger et al. (2022), a direct correlation is observed: as ESG market sentiment increases, the influence of ESG on measures of misvaluation becomes more pronounced. Focusing on the context of ESG financial bubbles, the impact of ESG sentiment on financial bubbles can manifest in divergent directions: boom or crash. Hence, it becomes essential to distinguish this impact for each scenario to assess the influence of sentiment on

financial bubbles (Van Eyden et al., 2023). Given the growing significance of sustainable investments, the continuous flow of information directing capital towards high ESG-rated investment objectives might elevate misevaluation, regardless of existing levels. Specifically, this could exacerbate the ongoing overvaluation of companies as market valuation moves further away from their fair value. On the other hand, in the case of undervalued stocks, market valuation is anticipated to surge concerning actual value due to increased capital inflow associated with ESG commitment. Thus, we test the second additional hypothesis:

- $\mathbf{H}_{2a}$: *Positive sentiment increases existing overvaluation;*
- $\mathbf{H}_{2b}$: *Negative sentiment influences contributing to the deflation of inflated asset prices following a market bubble.*

3. Reserach design

3.1. Data

In this section, we present the data utilised in our study. First, we detail the sources and characteristics of the data related to ESG financial markets. Subsequently, we show the data used to build the ESG attention index.

3.2. ESG stock market

To represent the climate performance indicator, i.e., the ESG financial markets (Khalfaoui et al., 2022), we use the MSCI ESG Leaders asset class. These financial indexes are weighted average indexes consisting of firms with high Environmental, Social, and Governance (ESG). Hence, they capture and reflect the dynamics of the ESG investment market (Chen and Lin, 2022; Cepni et al., 2023). To have a complete overview of the ESG financial markets, we focus our analysis on the context of the United States (USA), Europe (EU), and Emerging Markets (EM) (like Akhtaruzzaman et al., 2022). Therefore, we selected the following indices at the weekly level from Datastream: MSCI USA ESG LEADERS, MSCI EUROPE ESG LEADERS and MSCI EMERGING MARKET ESG LEADERS. Given data availability, our article covers the sample period of 6 September 2010 to 30 March 2023.[1]

3.2.1. ESG sentiment index

As a proxy for ESG investor attention, we use the Google Search Volume Index (GSVI). The GSVI is able to capture the attention of researchers who use keywords to search the internet (Da et al., 2011). The GSVI serves as a quantitative sentiment indicator derived from Google Trends, capturing the volume of searches related to specific keywords or topics over a defined period. As a proxy for ESG investor attention, GSVI leverages the concept that increased search activity around ESG-related terms reflects heightened interest and attention from market participants in ESG-related investments, companies, or themes. This attention is manifested through internet search behaviour, highlighting the growing significance of ESG considerations in investment decision-making. Extensive scholarly research spanning various disciplines such as finance, economics, and behavioural studies has investigated the utility of GSVI as a gauge for investor attention and its subsequent impact on financial markets. Moreover, using Google search data offers a uniform and standardized approach to calculating ESG sentiment across diverse countries. Unlike other sentiment analysis methods limited by specific data sources (like newspapers, Yu et al., 2023) or countries (Santi, 2023; Dhasmana et al., 2023), Google data provides a broader and consistent representation of ESG-related sentiments. The uniformity in using Google data as a source for sentiment analysis ensures consistency and enables direct comparisons between countries, facilitating comprehensive cross-country evaluations. Furthermore, the GSVI index presents an objective and unbiased source of information devoid of operational error and human response biases. This characteristic enhances the reliability and credibility of GSVI as an indicator of media attention.

Studies such as those by Da et al. (2015), Hamid and Heiden (2015), Dimpfl and Jank (2016), Brochado (2020), Enoksen et al. (2020), Bonaparte (2021), Ding et al. (2022), and Santi (2023) have established the viability of using Google Trends as a proxy for investor attention. Moreover, several prominent studies within the recent literature (Bank et al., 2011; Vlastakis and Markellos, 2012; Han et al., 2017; Swamy et al., 2019; Hsieh et al., 2020; Chen et al., 2021; Chen and Craig, 2023) provide support for the 'attention theory', showing a positive correlation between Google Trends and stock performance. Therefore, according to the literature, we can use Google Trends as a proxy for ESG investor attention.

Following Bonaparte (2021) and Kerkemeier and Kruse-Becher (2022), we use the GSVI keyword "ESG" to measure investors' attention to this topic.[2] Weekly GSVI data are extracted from Google Trends following the approach of Bleher and Dimpfl (2019)[3]

3.3. Methodology

3.3.1. The multi-scale log-periodic power law singularity framework

The log-periodic power law singularity (LPPLS) framework is a helpful method for identifying financial bubbles. The LPPLS model assumes that during a bubble, the price of a financial asset diverges from its fundamental value (Sornette, 2017; Demirer et al., 2019). The model supposes the existence of two types of agents in the market. On the one hand, there are traders who rely on rational expectations based on economic fundamentals. On the other hand, there are "noise traders" who act impulsively and irrationally by overreacting to news about the financial instrument. Therefore, the framework combines two common traits of bubbles: transient super-exponential power law growth and accelerating log-periodic fluctuations in volatility (Shu and Zhu, 2020). According to Sornette et al. (2015) and Shu and Zhu (2020), the LPPLS is based on three foundations: (1) the economic theory of bubbles, (2) behavioural finance (imitation and herding bias), and (3) the mathematical parametrization of the LPPLS model.

Mathematically, the LPPSL framework, namely the Johansen–Leoit–Sornette (JLS; Sornette et al., 1996), presupposes that the logarithm of the price $p(t)$ is given by:

$$\frac{dp}{p} = \mu(t)dt + \sigma(t)dW - kdj \tag{1}$$

where $\mu(t)$ is the expected stock return, $\sigma(t)$ is the volatility, dW is the infinitesimal increment of a standard Wiener process (with zero mean and variance equal to dt), and dj represents a discontinuous jump with $j = 0$ before the price crash and $j = 1$ after the collapse. The parameter k quantifies the magnitude of a possible market crash.

Following Demirer et al. (2019), we can describe the crash hazard rate caused by "noise traders" as follows:

$$h(t) = \alpha(t_c - t)^{m-1}(1 + \beta\cos(\omega\ln(t_c - t) - \phi)) \tag{2}$$

where α, β, ω, and t_c are parameters. Imitative behaviour by noise traders is determined by $\alpha(t_c - t)^{m-1}$, while t_c shows the critical time

[1] We tried to select the most comprehensive possible time range. However, the earliest available data for the MSCI EUROPE ESG LEADERS index starts on 08/31/2010. Therefore, we have chosen that initial period.

[2] We also use alternative keywords related to ESG, for example, "Environmental, social, and corporate governance". The results remain robust, and they are available upon request.

[3] The Google Search Volume Index at the aggregate European and Emerging Market levels are unavailable. Therefore, we built the European Google Trend index and Emerging Market Google Trend index as a weighted average of the constituent countries of the MSCI ESG Europe index and MSCI ESG Emerging Market index, respectively.

at which the bubble is most likely to burst. The no-arbitrage condition dictates that the excess return $\mu(t)$ during a bubble phase is proportional to the percentage of collapse risk. By integration, we obtain the price trajectory on a logarithmic basis during a bubble phase provided the collapse has not yet occurred (Filimonov and Sornette, 2013), i.e.:

$$\ln E[p(t)] = A + B(t_c - t)^m + C(t_c - t)^m \cos(\omega \ln(t_c - t)^m - \phi) \quad (3)$$

where A is the expected value ln(price) at critical time t_c, B denotes the amplitude of the power law acceleration, while C captures the relative magnitude of the log-periodic oscillations. Finally, $0 < m < 1$ is the power parameter, while ω denotes the angular magnitude of the oscillation. The model makes it possible to distinguish positive or negative bubbles separately. For example, positive bubble regimes are generally characterized by $0 < m < 1$ and $B < 0$. The first condition $m < 1$ highlights the existence of a singularity, while $m > 0$ guarantees that the asset price remains finite at the critical time (t_c). The second condition $B < 0$ expresses that the price actually grows exponentially towards t_c (positive bubble), while $B > 0$ indicates a negative bubble.

According to Filimonov and Sornette (2013), the Eq. (3) can be reformulated by deleting the nonlinear parameter ϕ, hence:

$$\ln E[p(t)] = A + B(f) + C_1(g) + C_2(h) \quad (4)$$

where $f = (t_c - t)^m$, $g = (t_c - t^m)\cos[\omega \ln(t_c - t)]$, and $h = (t_c - t^m)\sin[\omega \ln(t_c - t)]$. This transformation means the LPPLS model can be calibrated to the price time series using the ordinary least squares method (OLS). Therefore, the OLS is used to estimate the three nonlinear parameters (t_c, m, ω) and the four linear parameters (A, B, C_1, C_2).[4]

Finally, following Demirer et al. (2019) and Van Eyden et al. (2023), we compute multiple timescales varying bubbles. Specifically, we calculate short-, medium- and long-run horizons. The short-term corresponds to estimation windows from 1 to 3 months, the medium-term represents the time windows from 3 months to 1 year, and finally, the long-term corresponds to estimation windows from 1 year to 2 years. This distinction allows us to get a diagnosis of how strong the LPPLS bubble structure is on the respective time scales. For example, if the short indicator is significant while the medium and long are small, this would indicate that a bubble has formed recently, that is, in the past three months. Moreover, such a distinction allows us to capture different time scales of investment strategies, from 1 month to 2 years.

Our methodology is one of the most effective tools for detecting financial bubbles. As mentioned, the framework presented not only permits one to decouple the analysis of bubbles into different time scales but also allows one to focus on positive or negative bubbles separately. Bubble detection econometric approaches, such as the change-point method (Boubaker et al., 2022), bubble detection in real-time (Phillips et al., 2015), the regime-switching model (Nneji et al., 2013) and the local-martingale theory of bubbles (Chaim and Laurini, 2019), exhibit limitations in this regard, reaffirming the significance of the approach adopted in this paper. This distinction assumes importance as it provides the capability to evaluate the potential asymmetric effects of investor sentiment on ESG stock market bubbles.

3.3.2. Regression model

To investigate the ESG attention effect on ESG equity market bubbles, we estimate the following panel regression:

$$bubble_{i,t} = \beta_{0,i} + \beta_{1,i} sent_{i,t-1} + \beta_{2,i} Z_{i,t-1} + \varepsilon_{i,t} \quad (5)$$

where $bubble_{i,t}$ shows the stock positive (negative) bubbles at various timescales (short, medium and long), $sent$ denotes the ESG attention sentiment and $Z_{i,t}$ is the matrix of control variables. As suggested by the literature (e.g., Scheinkman and Xiong, 2003; Wang and Chen, 2019; Pan, 2020; Van Eyden et al., 2023), we include the share price volatility and the total volume as specific financial market control variables. Specifically, we include these variables following Scheinkman and Xiong's theory (Scheinkman and Xiong, 2003). Their framework shows that equity bubbles are linked to large trading volumes and high price volatility, suggesting a positive effect on asset price bubbles. Their theoretical framework, considering heterogeneous beliefs, supports this conclusion. Moreover, to take into account the macro-financial environment, we include the gold price, WTI oil price, and iBoox bond index. Finally, $\varepsilon_{i,t}$ is the idiosyncratic error term. According to the literature (Jean et al., 2016; Kingsley and Graham, 2017; Demirer et al., 2019; Santi, 2023), we use one-period lagged explanatory variables to reduce the potential endogeneity problem.

[4] Please see Sornette et al. (2015) and Demirer et al. (2019) for the full complete aspect of parametrization and optimization issues.

Table 1
Testing the residuals.

ESG market	ADF test
USA ESG	−3.68***
EUROPE ESG	−4.86***
EM ESG	−3.46***

Notes: This table reports the ADF test. The reported numbers are the t-statistics. The appropriate lag length for the ADF test is selected using the Schwarz-Bayesian criterion (SC).
*** Indicates a 1% significance level.

4. Empirical evidences

In this section, first, we identify the financial bubbles of the ESG financial market by the LPPLS confidence indicator. Second, we test the social (financial) bubble hypothesis by relating the Google Trend ESG attention indexes and the price bubbles by a panel regression model.

4.1. Testing stationarity of residuals

Before identifying the bubbles with the LPPLS model, we need to check the stationarity of the model residuals (Eq. (3)). In fact, the non-stationarity of the residuals could indicate spurious regression. As Lin et al. (2014) suggested, the LPPLS estimation residuals should follow a stationary process of mean reversal. In Table 1, we report the Augmented Dickey–Fuller Unit Root Test (ADF) stationarity test (Dickey and Fuller, 1979). As we can note, the regressed models correctly specify the residuals in the ADF test regression for each market, i.e. the residuals are stationary. This means that residuals of the LPPLS model follow a stationary process of mean reversal. Therefore, our model is well-specified, i.e., the LPPLS signature is statistically significant.

4.2. Identification of financial bubbles

Figs. 1–3 display the empirical estimation of the LPPLS confidence indicator. The left side of the Figures shows the estimate of positive bubbles, and on the right side are the indicators of negative bubbles (crashes). Short-term, medium-term and long-term bubbles are shown in orange, blue, and purple (right scale), respectively, along with the MSCI ESG log(price) in black (left scale). The confidence level of the LPPLS bubble model has a range of $[0; 1]$. This means that when the indicator is close to 1, the LPPLS pattern is present in almost all time windows, that is, all time scales (Sornette et al., 2015; Demirer et al., 2019). This indicator, for example, greater than a filter of 10% (as suggested by Shu et al., 2021), indicates that the detected LPPLS signature is relatively robust to the selection of onset time so that the price trajectory can be confirmed as a bubbling regime. On the other hand, an indicator close to zero suggests possible signal fragility, hence the price trajectory is unlikely to be in a bubble regime.

A positive bubble is associated with a super-exponential price growth trend towards t_c and ends with a regime change (i.e., crash).

On the other hand, negative bubbles show an accelerating price decline that ends with a regime change (i.e., price rebound). In fact, the rebounding price trend may discourage some investors from investing. This, in turn, causes further declines (Shiller, 2000; Goetzmann et al., 2016). Temporary spikes in pessimism (exuberance) may typically show signs of mean-reversion, but at the extreme, they may show signs of bullish (bearish) market bubbles (Goetzmann and Kim, 2018).

Focusing on positive bubbles, we can observe three clusters of medium and long bubbles between the end of 2013 and the end of 2014, between 2017 and 2018, and between 2020 and 2022 for all the ESG markets. Climate policies have had a significant impact on the performance of ESG indices, thus on bubble formation. In fact, we can note how policy events related to climate change, such as the Paris Agreement (2015), the United Nations conferences on climate change (2013–2021), the IPCC reports (2014–2023), and the National Climate Assessment reports (2018) have had a significant impact on the dynamics of equities. In addition, China and the USA have proposed carbon neutrality targets (end of 2020), contributing to positive bubbles on the stock indices of MSCI ESG leaders. These results are in line with literature (Antoniuk and Leirvik, 2021; Angelini et al., 2022; Miglietta et al., 2022; Cepni et al., 2023), which shows that mean and risk spillovers of sustainable financial markets are driven principally by climate change events.

Concentrating on negative bubbles, it is interesting to note that after the crash, we observe strongly negative LPPLS values signalling a boom in these markets. In the U.S. context, we can see a strong market crash near 2016. This coincides with Trump's (2016) election period. This dynamic is not unexpected given that former U.S. President Donald Trump supported the repeal of the Climate Action Plan, the Waters of the U.S. rule, the Paris Climate Agreement, and regulatory environment reform during his presidential campaign (Cepni et al., 2023; Santi, 2023). Focusing on the European context, we can see a negative spike in the index price, that is, the presence of negative bubbles. This crash refers mainly to the Russian–Ukrainian conflict, which has spread strong uncertainty to the financial markets (Ahmed et al., 2022; Yousaf et al., 2022). Finally, at the Emerging Markets level, we see a significant rally signalled by a negative medium-term LPPLS value in late 2018 to early 2019, likely associated with the China-United States trade war. Finally, a negative short-, medium-, and long-term LPPLS value is observed from late 2021 to late 2022. One possible explanation is the introduction of a carbon tax placed by the Chinese government to mitigate the impact of carbon levies at the European border and reintroducing anti-COVID-19 measures, i.e., COVID-Zero policies (Liu, 2022). Since 2022, the impact of the Russa-Ucraine war on the EM economy firms has been visible. In fact, several studies (Jiang et al., 2023; Saharti et al., 2024) have shown how war and geopolitical conflicts have greatly affected sustainable investments, especially in emerging economies.

Interestingly, we find that, as with the medium-term indicators preceding the long-term ones, the short-term ones tend to precede the medium-term ones. These findings support the conclusion of Demirer et al. (2019) and Van Eyden et al. (2023), which show the maturation of a financial bubble occurs on several different time scales.

4.3. Testing the social hype bubble hypothesis

Once we have identified positive and negative bubbles on different time scales, we test the social bubble hypothesis in this section. In particular, we examine the relationship between ESG attention sentiment and financial bubbles by computing a panel regression model. In Table 2, we report the estimation results between ESG sentiment and multi-scale positive bubble, while Table 3 shows the empirical findings for the multi-scale negative bubble indicators.

Generally, ESG searches and transactions positively affect bubble behaviour in all panel models. It can be seen from Table 2 that both Google ESG indexes exert a positive and statistically significant impact on positive bubbles in ESG markets in the short and medium term. By including the specific control variables (Model 2,5,8) and macro environment variables (3, 6, 9), the results remain qualitatively the same. On the other hand, the results in Table 3 show how the Google ESG index has a negative impact on negative bubbles in the short, medium, and long run. The findings are statistically significant in the bivariate case (Model 1, 4, 7) and after controlling for other assets (Model 2, 3, 5, 6, 8, 9). Thus, higher ESG sentiment values tend to increase positive LPPLS indicators and reduce the LPPLS negative indicators. It is interesting to note that higher sentiment can actually instigate the crash even in the long run, highlighting its long-term effect. Therefore, this phenomenon could be explained by the hypothesis that the pessimism of noisy traders can shake the financial markets (Huynh et al., 2021).

For the effects of the specific controls, the analysis provides evidence that volatility and trading volume play pivotal roles in determining the emergence and dynamics of financial bubbles. This finding aligns with the research conducted by Pan (2020) and Van Eyden et al. (2023), who demonstrated that volatility negatively impacts positive LPPLS-CI indicators and positively affects negative LPPLS-CI indicators. This observation corroborates the notion that bubbles are more likely to develop during periods of heightened market volatility. The results of Narayan et al. (2013) and Wang and Chen (2019) further support this conclusion, underscoring the significance of incorporating volatility as a crucial determinant in models aimed at predicting and understanding bubble dynamics. For instance, our analysis of short negative bubbles reveals that the coefficients of volatility and trading volume are positive and statistically significant at the 5% and 1% levels, respectively. This implies that volatility and trading volume play a key role in the existence of these short-term equity bubbles.

Overall, the empirical findings are perfectly in line with Van Eyden et al. (2023), which find that sentiment has opposite effects depending on the bubble considered (positive and negative). In fact, on the one hand, the positive bubble indicator signals rapid growth in stock markets before a crash. On the other hand, a negative bubble indicator captures recovery after a crash. This implies that when sentiment changes, the probability of the occurrence of positive and negative bubbles in stock markets increases. For example, a positive bubble could appear when investors believe that the ESG markets will continue to rise. This can lead to a feedback loop between sentiment and ESG price. Because investor sentiment is high, the more investors invest in the ESG market, the more demand increases, and the more price rises. On the other hand, if we consider a reduction in investor sentiment, it negatively affects the ESG markets. Again, more pessimistic investors, more investors divest in the ESG market, the more offer increases, and the more prices decline. Our finding supports the view that sentiment is an important driver of boom-bust cycles in the financial markets (e.g., Schmeling, 2009; Zouaoui et al., 2011; Dimpfl and Jank, 2016; Foglia and Angelini, 2020; Brochado, 2020; Chen et al., 2022; El Ouadghiri et al., 2021).

4.4. Robustness check

In this subsection, we compute robustness checks to further investigate the relationship between financial bubbles and ESG sentiment. For this purpose, following Pan (2020) and Gupta et al. (2023), we apply a Vector Autoregressive (VAR) model in order to investigate the response of short, medium and long-term bubbles (positive and negative) to shock in ESG sentiment.[5]

In Fig. 4, we report the impulse response functions (IRFs) for each ESG financial market related to an ESG sentiment shock on positive and negative bubbles in the short, medium, and long term, respectively.[6]

[5] The lag is chosen using the Schwarz Bayesian Criterion (BIC). Based on this test, the adequate number of lags is 1.

[6] The response of long-term negative bubbles for the USA market was not estimated because they were not found (please see Fig. 1).

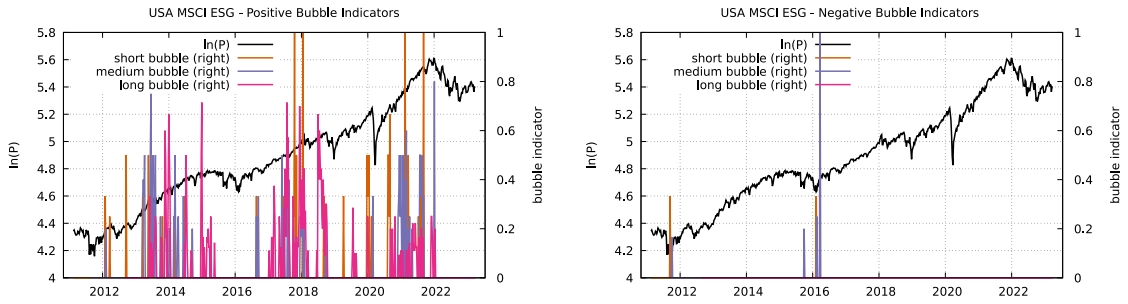

Fig. 1. USA MSCI ESG Multiscale LPPLS Indicators. *Notes:* Positive (left side panel) and negative (right side panel) multi-scale LPPLS Confidence bubble indicator. Short-term, medium-term, and long-term bubbles are shown in orange, blue, and purple (right scale), respectively. The USA MSCI ESG log(price) is displayed in black (left scale) from 6 September 2010 to 30 March 2023.

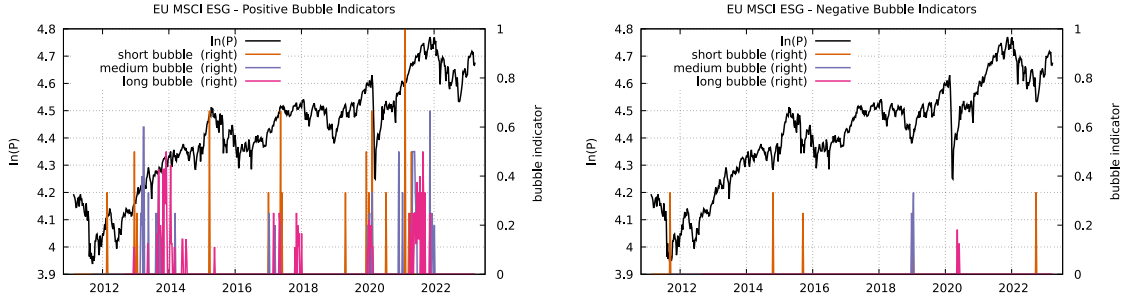

Fig. 2. EUROPE MSCI ESG Multiscale LPPLS Indicators. *Notes:* Positive (left side panel) and negative (right side panel) multi-scale LPPLS Confidence bubble indicator. Short-term, medium-term, and long-term bubbles are shown in orange, blue, and purple (right scale), respectively. The EUROPE MSCI ESG log(price) is displayed in black (left scale) from 6 September 2010 to 30 March 2023.

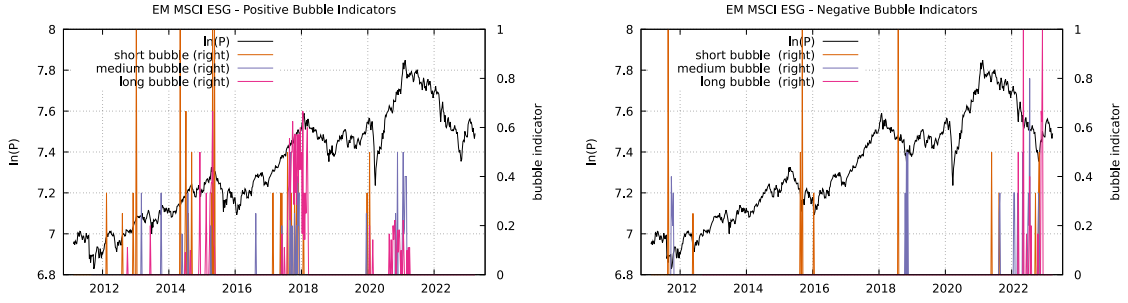

Fig. 3. EM MSCI ESG Multiscale LPPLS Indicators. *Notes:* Positive (left side panel) and negative (right side panel) multi-scale LPPLS Confidence bubble indicator. Short-term, medium-term, and long-term bubbles are shown in orange, blue, and purple (right scale), respectively. The EM MSCI ESG log(price) is displayed in black (left scale) from 6 September 2010 to 30 March 2023.

Table 2
Sentiment and Positive bubble.

Positive bubble	Short bubble			Medium bubble			Long bubble		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.017***	0.108**	−0.849***	0.021***	0.199	−1.618*	0.038**	0.046**	−0.865***
	(0.002)	(0.044)	(0.235)	(0.002)	(0.081)	(0.420)	(0.008)	(0.008)	(0.262)
ΔESG-GT$_{t-1}$	0.009***	0.010**	0.009**	0.002*	0.001*	0.001*	−0.001	−0.001	−0.001
	(0.000)	(0.004)	(0.003)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.006)
Volatility		−0.073***	−0.526*		−0.072**	−0.162*		−0.144**	−0.642*
		(0.027)	(0.310)		(0.008)	(0.091)		(0.023)	(0.372)
Trade		−0.0039**	−0.004**		−0.001	−0.007*		−0.004	−0.005**
		(0.001)	(0.001)		(0.001)	(0.002)		(0.003)	(0.002)
Macro control	NO	NO	YES	NO	NO	YES	NO	NO	YES
Obs.	1896	1896	1896	1812	1812	1812	1656	1656	1656
R-squared	0.001	0.01	0.02	0.001	0.01	0.02	0.001	0.01	0.04

Notes: Robust standard errors are reported in parentheses. Δ shows the change (first-difference) of the Google Trend Index. The macro control variables are the iBoxx bond index, the gold price, and the crude oil WTI price.

* Indicate 10% significance level.

** Indicate 5% significance level.

*** Indicate 1% significance level.

Table 3
Sentiment and negative bubble (crash).

Negative bubble	Short bubble			Medium bubble			Long bubble		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.004***	−0.068***	0.258**	0.005	−0.076	0.204	0.003	0.002	0.204*
	(0.000)	(0.022)	(0.121)	(0.003)	(0.026)	(0.101)	(0.002)	(0.001)	(0.109)
ΔESG-GT$_{t-1}$	−0.005**	−0.006**	−0.006**	−0.003*	−0.002**	−0.003*	−0.001*	−0.001**	−0.001**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Volatility		0.343**	0.244*		0.183	0.474		0.155	−0.116
		(0.014)	(0.014)		(0.205)	(2.252)		(0.214)	(0.156)
Trade		0.003***	0.003***		0.003*	0.003*		0.005	0.004)
		(0.000)	(0.000)		(0.001)	(0.001)		(0.004)	(0.003)
Macro control	NO	NO	YES	NO	NO	YES	NO	NO	YES
Obs.	1896	1896	1896	1812	1812	1812	1656	1656	1656
R-squared	0.001	0.01	0.02	0.001	0.01	0.02	0.001	0.01	0.03

Notes: Robust standard errors are reported in parentheses. Δ shows the change (first-difference) of the Google Trend Index. The macro control variables are the iBoxx bond index, the gold price, and the crude oil WTI price.

* indicate 10% significance level.

** indicate 5% significance level.

*** indicate 1% significance level.

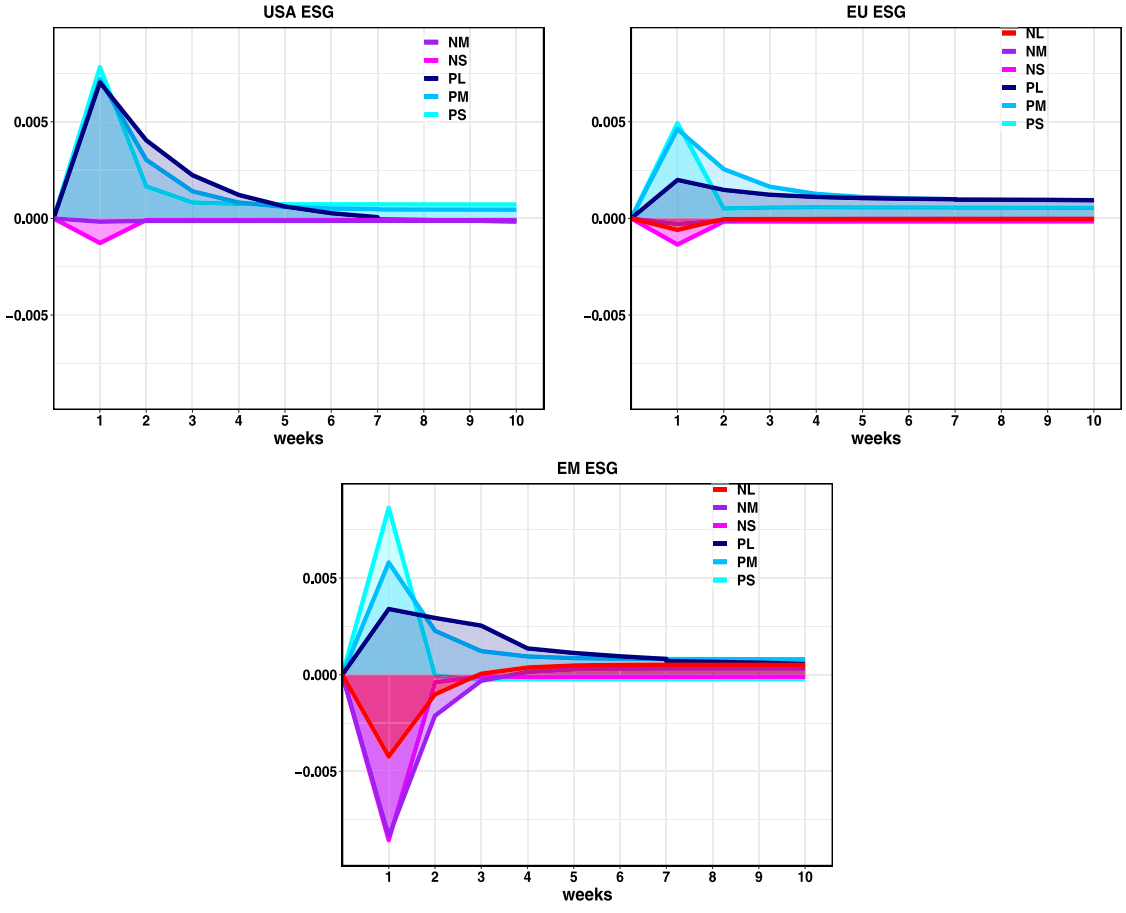

Fig. 4. Impulse response for each market. *Notes:* Impulse response function for positive short-term (PS), medium-term (PM) and long-term bubbles (PL), and negative short-term (NS), medium-term (NM) and long-term bubbles (NL), respectively.

The results show, consistent with the analysis above, that an ESG sentiment shock tends to increase positive LPPLS indicators, in contrast, it reduces the LPPLS negative indicators. In the short term, the analysis suggests that ESG sentiment has a notable impact on the acceleration of positive and negative bubbles, aligning with the findings that volatility and trading volume contribute significantly to short-term equity bubbles. The observed reduction in negative indicators during this period further supports the idea that ESG sentiment acts as a catalyst for market optimism, potentially averting or mitigating negative bubble development in the immediate aftermath of a sentiment shock. This result means that sentiment contributes to the market's rapid growth before the crash and causes it to rebound faster when in a bearish condition. As we can observe, in the medium and long run, the sentiment shock shows that when markets are in bullish conditions (positive bubble), the crash effect becomes stronger than the recovery effect. This suggests that, over a more extended timeframe, the influence of ESG sentiment

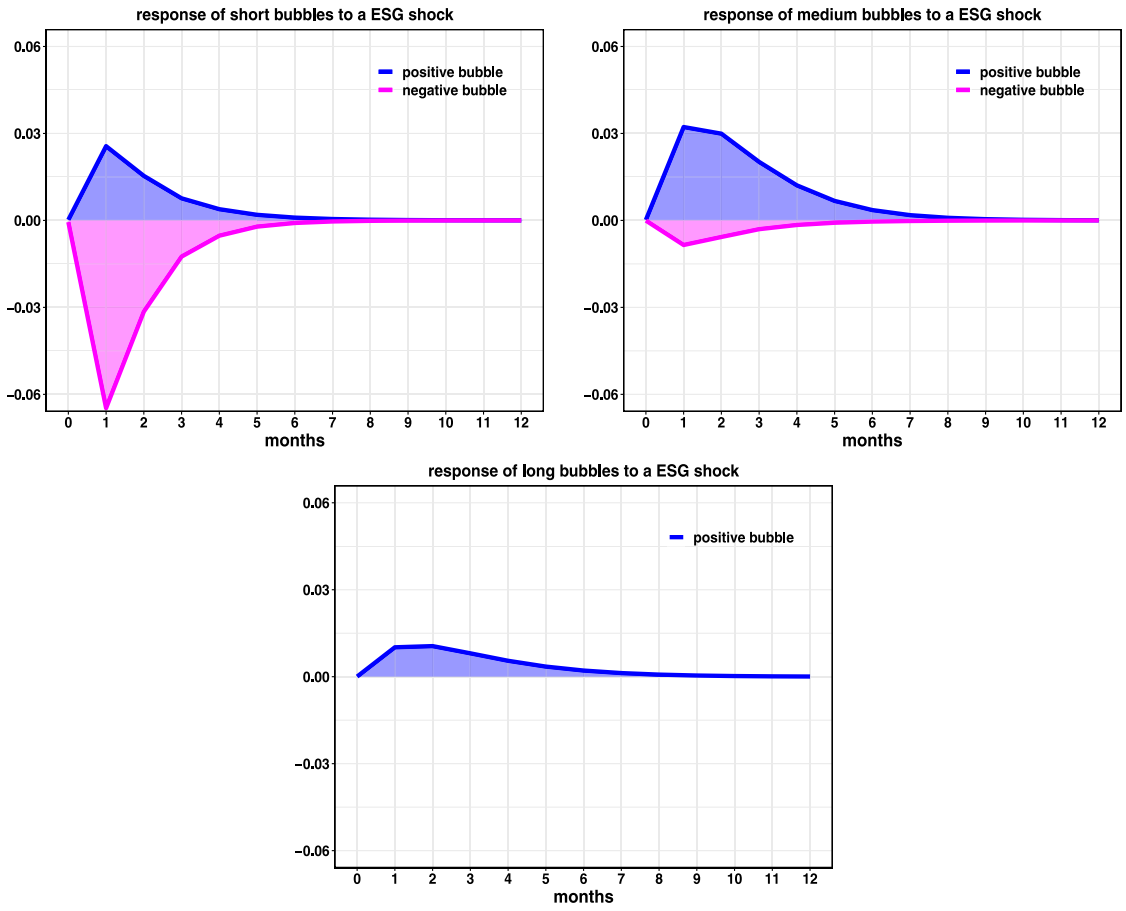

Fig. 5. Impulse response for USA. *Notes:* Impulse response function for short-term, medium-term and long-term bubbles, respectively. The positive bubble response is displayed in blue, while a negative bubble response is displayed in magenta.

may be more impactful in market downturns, leading to a stronger negative impact on bubble dynamics.

4.4.1. Sensitivity analysis

Now, we test the sensitivity of our results using the ESG market sentiment index developed by Santi (2023). Since the index refers to the USA context, we focused our analysis only on this market at the monthly level. In addition, because the index runs from January 2010 to September 2019, we had to shorten the period of investigation.[7]

The impulse response functions (Fig. 5) reveal a clear relationship between ESG sentiment shocks and LPPLS indicators. Consistent with prior analysis, we find a similar pattern of the response. In particular, we detect that an ESG sentiment shock tends to increase positive LPPLS indicators while reducing negative indicators, particularly in the short term. This implies that ESG sentiment contributes to rapid market growth before a potential crash and facilitates a quicker rebound during bearish conditions.

5. Discussion of results

Does every cloud (bubble) have a silver lining? According to the literature (Gisler et al., 2011; Lehnert, 2022; Giorgis et al., 2022), we can interpret financial bubbles from a dual perspective, namely financial and social. While on the financial side, a bubble means a prolonged deviation from its fundamental value (price), on the social side, a bubble derives from people's attitudes and preferences towards a particular good/asset, i.e., the perception of it.

Financial bubbles occur when asset prices inflate significantly beyond their intrinsic value due to irrational exuberance or speculation. This often results in a rapid price rise followed by a sharp decline, leading to significant financial losses for investors. Several factors, such as excess liquidity, low interest rates, lack of supervision, speculation effects, and herd behaviour, can cause financial bubbles. In addition, financial bubbles tend to emerge in sectors perceived as "hot" and promising, causing an influx of investment and a subsequent price surge (such as green finance and sustainable markets). The bursting of a financial bubble can have significant consequences for both investors and the real economy. In some cases, financial bubbles can also lead to a widespread loss of confidence in the financial system and government institutions (Aoki and Nikolov, 2015). On the other hand, the formation of some bubbles can act as important catalysts for social innovation. In fact, bubbles have accelerated the development and adoption of transformative technological innovations (Ghosh et al., 2022; Huber and Sornette, 2022). As pointed out by Giorgis et al. (2022), "exceptional enthusiasm leads to imitation and herd behaviour, which, in turn, creates positive feedback loops" on the real economy. Hence, a "social bubble" is considered relatively positive in the long run about economic development (Lehnert, 2022).

The growing interest in ESG investments has raised concerns about the possibility of an ESG social bubble. This may lead to an overvaluation of ESG investments, similar to the overvaluation of Internet companies during the *dot-com bubble* (BIS, 2021). One potential consequence of an ESG social bubble is the overvaluation of companies that claim to be ESG-friendly but may not implement significant changes in their operations. This could lead to misallocation of capital and

[7] The monthly ESG sentiment index is kindly downloadable directly from the website of Professor Caterina Santi: https://www.caterinasanti.com/research

undermine the legitimacy of the ESG movement. In addition, an ESG social bubble could lead to a loss of confidence in ESG investments if they are perceived as a short-term (speculative) fad rather than a long-term investment strategy. However, while ESG bubbles can have negative effects, such as potential misallocation of capital, there are also potential positive effects on the economy that can result from ESG investments. First, ESG investments can foster positive change in companies and sectors, encouraging them to adopt more sustainable practices and reduce their negative impact on the environment and society. This can translate into long-term economic benefits, including less resource depletion, thus less impact on the climate. Second, ESG investments can improve companies' financial performance. By adopting sustainable practices, companies can reduce risks related to environmental and social issues, resulting in better financial performance in the long run. This can benefit investors, the economy and the fight against climate change.

Our research shows how the ESG financial market experiences different phases of financial bubbles (Figs. 1–3) and how they are dictated by sentiment attention about these markets (Tables 2–3). Therefore, while ESG investments have the potential to drive social and environmental change, contributing to a more sustainable economy, investors must remain vigilant about the possibility of an ESG financial bubble, as suggested by BIS (2021). As investor sentiment shows positive effects on bubbles, investors and policymakers are advised to be careful when the level of sentiment is rising. The growth could imply an imminent market crash. The widespread search for yield that is going on in these financial markets may thus be due more to the herd effect combined with the "attention-grabbing" hypothesis (Barber and Odean, 2008) than the sustainable investment perspective. The media play a significant role in forming market consensus opinions and evoking this "herd" behaviour (Strycharz et al., 2018). This effect shows how news plays a crucial function in influencing investment choices. In fact, as the literature on this subject highlights, individual investors are more inclined to invest in stocks that have been the subject of news. Therefore, as media attention to the ESG increases, investors' belief in these stocks increases. Policymakers should implement policies that keep investor social sentiment in check during bullish regimes of ESG stock markets. On the other hand, by critically evaluating investment opportunities and avoiding "common (hype) thinking", investors can contribute to the long-term sustainability of the ESG movement.

6. Conclusion

In this research, we analysed the financial risks of environmentally friendly investments. First, we used the log-periodic power law singularity (LPPLS) approach to recognize multi-scale positive and negative bubbles in MSCI ESG indices in the USA, Europe, and Emerging Markets contexts. Second, we applied a panel regression to analyse the impact of ESG attention sentiment on bubble indicators.

The results show evidence of financial bubbles in ESG financial markets. In particular, we identified positive and negative bubbles in correspondence with important climate events. Second, we showed how financial bubbles are driven by ESG sentiment derived from Google Trend indicators.

Our analyses lead us to two main conclusions. First, we find the presence of bubbles in ESG markets, confirming the assumptions of the BIS (2021) report. This leads to a clear attention focus on the dynamics of this market. Second, we confirm that sentiment (ESG attention) has predictive power on positive and negative bubbles at different time scales. This means that higher sentiment is associated with a positive bubble and negative sentiment with a crash. Therefore, these results align with the theory that sentiment causes financial turmoil. Our findings contribute to monitoring and understanding environmentally friendly investment dynamics. The ability to predict bubbles is necessary to have complete and deep information about the risk of ESG investments. Therefore, our findings can help investors and policymakers. On the one hand, policymakers should implement policies that keep investor social sentiment in check during bullish and bearish regimes of ESG stock markets. On the other hand, when the ESG market is in a bubble phase or when ESG sentiment is high, investors can avoid taking long positions. Otherwise, they can take short positions before the bubble bursts or its price declines substantially.

A future research development would be to test the effects of the social ESG bubble on the real economy. This new paper will shed light on financial bubbles' long-term positive or negative spillover effects.

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We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

CRediT authorship contribution statement

Matteo Foglia: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Federica Miglietta:** Conceptualization, Supervision, Writing – original draft, Writing – review & editing.

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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