Finance Research Letters 56 (2023) 104135

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

SFDR, investor attention, and European financial markets

Giuliana Birindelli, Helen Chiappini *, Raja Nabeel-Ud-Din Jalal

Department of Management and Business Administration, G. d'Annunzio University of Chieti-Pescara, Viale Pindaro 42, 65127, Pescara, Italy

ARTICLE INFO

Keywords:
Sustainable finance
SFDR
Google trends
Nonparametric causality-in-quantiles
Equity market indexes

ABSTRACT

This study investigates whether investor attention to the Sustainable Finance Disclosure Regulation (SFDR) leads European financial markets during the years 2019–2022. Using the nonparametric causality-in-quantiles method, results suggest investor attention has a strong predictive power on the financial markets, mostly during bearish and normal market conditions. Findings are robust to several alternative tests. Our research contributes to the literature on the link between investor attention and financial markets, and on the sustainable finance research stream, with relevant implications for asset managers.

1. Introduction

Our paper investigates whether investor attention toward the Sustainable Finance Disclosure Regulation (SFDR, EU 2019/2088) is a predictor in European financial markets over different market conditions.

The SFDR is part of the European effort to encourage investor confidence in sustainable investments, to reduce greenwashing, and, in turn, increase sustainable practices.[1] The SFDR requires financial actors in Europe (banks, insurers, asset managers, and investment firms) to disclose two levels of social and environmental information: entity and product level disclosure.[2]

* Corresponding author.
E-mail address: helen.chiappini@unich.it (H. Chiappini).

[1] As motivation for the SFDR, European regulators note that "In the absence of harmonised Union rules on sustainability-related disclosures to end investors, it is likely that diverging measures will continue to be adopted at national level and different approaches in different financial services sectors might persist. Such divergent measures and approaches would continue to cause significant distortions of competition because of significant differences in disclosure standards. […] Divergent disclosure standards and market-based practices make it very difficult to compare different financial products, create an uneven playing field for such products and for distribution channels, and erect additional barriers within the internal market. Such divergences could also be confusing for end investors and could distort their investment decisions. […] Furthermore, the lack of harmonised rules relating to transparency makes it difficult for end investors to effectively compare different financial products in different Member States with respect to their environmental, social and governance risks and sustainable investment objectives. It is therefore necessary to address existing obstacles to the functioning of the internal market and to enhance the comparability of financial products in order to avoid likely future obstacles" (EU 2019/2088 p. L317/3).

[2] At the entity level, the financial actors are required to publish information on sustainability risk integration in their investment decisions (Article 3 EU 2019/2088), including whether their financial decisions affect sustainability or not (Article 4 EU 2019/2088) and whether remuneration policies are integrated with sustainability risk (Article 5 EU 2019/2088). The product level disclosure implicitly recognizes three different levels of "ESG-integration" (Becker et al., 2022) in sustainable financial products and progressive levels of disclosure. Thus, Article 6 of EU 2019/2088 covers products considering the sustainability risk in the investment decision and how it impacts the related financial returns; products under Article 8 of EU 2019/2088 promote investments considering environmental, social and governance features and thus, disclosure provides information on how financial products satisfy these aims; lastly, products under Article 9 of EU 2019/2088 have a sustainability objective and disclosure should inform how the products align to the objective. If the product is designed using a sustainability index as a benchmark, related disclosure should provide information on how the index is designated as a benchmark and on compliance with the index objective.

https://doi.org/10.1016/j.frl.2023.104135
Received 1 March 2023; Received in revised form 6 May 2023; Accepted 22 June 2023
Available online 28 June 2023
1544-6123/

Literature in this field is scarce. Becker et al. (2022) show that the SFDR has increased the mutual fund ESG scores and has led to a large fund inflow, while Cremasco and Boni (2022) find there is "category fuzziness" of the investment funds self-identified under Articles 6, 8, and 9 of the SFDR. This issue suggests that SFDR disclosure is still in its infancy and calls for careful supervision by the European authorities. Thus, while studies investigating the effectiveness of the SFDR seem relevant, albeit premature given the ongoing regulatory process, analyzing whether SFDR investor attention leads financial markets, would provide timely information.

Since Da et al. (2011) pioneering research, investor attention on certain assets (e.g., cryptocurrency and green finance) or topics (e.g., the Coronavirus pandemic and the Ukraine conflict) expressed through search engines (such as Google and Baidu) has been recognized as a predictor of equity market prices (Austmann and Vigne, 2021; Corbet et al., 2020; Costola et al., 2021; Dastgir et al., 2019; Halousková et al., 2022). Indeed, a growing investor searches for such topics or events generate pressure on market prices (Barber and Odean, 2008; Da et al., 2011) as the "internet has inevitably become the link between information and market price changes" (Wei et al., 2021, p. 2) over recent years. The theoretical mechanism explaining the relationship relates to the limited information that investors are able to process and thus, the more attention a topic receives and more it influences the price behavior (Barber and Odean, 2008).

Some exceptions, however, appear possible. The recent research by Bonaparte and Bernile (2023, pp. 1–2) finds that investor attention to cryptocurrency regulation does not affect cryptocurrency prices. This result is explained by investors who "overlay positive attitude towards crypto assets, making crypto a Wall Street Darling", therefore minimizing bad news regarding crypto regulation. Overall, the (positive or negative) nature of certain events or the (positive or negative) investor behavior drives the volume of searches and, in turn, investor expectations about the financial markets (Wei et al., 2021). Thus, based on the evidence of previous research, we pose that investor attention towards the SFDR – a regulation pushing financial actors to disclose their level of sustainable practices – affects European financial markets because of positive (negative) expectations on the reduction of greenwashing, improvements of sustainability practices and reflections on financial sector costs and overall value. However, sensitivity is lower (higher) during bullish (bearish) market conditions (Bonaparte and Bernile, 2023). In other words, during bullish (bearish) markets, regulation lowers (raises) prices due to the optimistic (pessimistic) expectations by investors.

Using the nonparametric causality-in-quantiles method, our findings reveal that investor attention to SFDR matters in price forecasting, mostly during bearish and normal market conditions. Thus, our study contributes to the body of knowledge in multiple ways. First, it enriches the nascent literature focusing on sustainable finance and the SFDR (e.g., Becker et al., 2022) and on its relationship with financial sector equity indexes. Second, it expands the growing strand of literature related to how investor attention predicts financial markets (Costola et al., 2021; Da et al., 2011; Gao et al., 2021; Halousková et al., 2022) by introducing a new perspective on investor attention toward sustainability regulations, while other studies focus on attention towards firms or exogenous events (e.g., COVID-19 or the Russia-Ukraine war). Finally, our study has practical implications for investors and asset managers given that our study provides a measure of market sensitivity (Bonaparte and Bernile, 2023) to the SFDR. The remainder of the paper is organized as follows. Section 2 presents the research design, while Section 3 presents and discusses the results. Finally, Section 4 concludes the study.

2. Research design

2.1. Method

To understand whether or not investor attention to SFDR predicts equity markets, we use the nonparametric causality-in-quantiles method. This method was proposed by Balcilar et al. (2017) based on consistent causality in quantiles (Jeong et al., 2012). The nonparametric causality in quantiles offers two main advantages: it enables researchers to analyze causality in different quantiles and it is robust to misspecification errors by using underlying dependency among variables (Balcilar et al., 2017; Bhatia and Basu, 2021; Raza et al., 2022). Model specification is included in Appendix A.

2.2. Data

To identify the investor attention towards the SFDR we use the Google Search Volume Index[3] (GSVI) based on Google Trends (Da et al., 2011; Bonaparte and Bernile, 2023). We chose the Google search engine over the others (such as Baidu) due to the popularity of Google as a globally used search engine, because of its documented use to predict financial markets (Anastasiou et al., 2022; Gao et al., 2021), and finally, because it offers a process of normalization (Jun et al., 2017).

The GSVI is created using several keywords (Aslanidis et al., 2022; Costola et al., 2021) representative of the SFDR (namely, Sustainable Finance Disclosure Regulation, SFDR, SFDR Regulations, SFDR sustainability, SFDR ESG, SFDR Article 6, SFDR Article 8, SFDR Article 9). We downloaded weekly Google Trends from January 2019 till April 2022 to compose our GSVI. Given the field of our analysis, our GSVI takes the name SFDR-GSVI. Fig. 1 shows weekly fluctuations in SFDR-GSVI.[4]

For the same period, we considered the closing price of the European financial sector stock market indexes (namely, S&P Europe

[3] The GSVI is a normalized indexed value (Jun et al., 2017), ranges from 0 to 100, and it is calculated by "dividing the number of searches for a given keyword into the total number of searches for a given time unit" (González-Fernández & González-Velasco, 2020, p. 409) and it is normalized by multiplying it by a scaling factor $F = 100/r^*$, where r is the fraction of the highest value of GSVI (Dergiades et al., 2015).

[4] Figure 1 shows an increase of Google searches in 2021 and 2022, as a consequence of the SFDR coming into force.

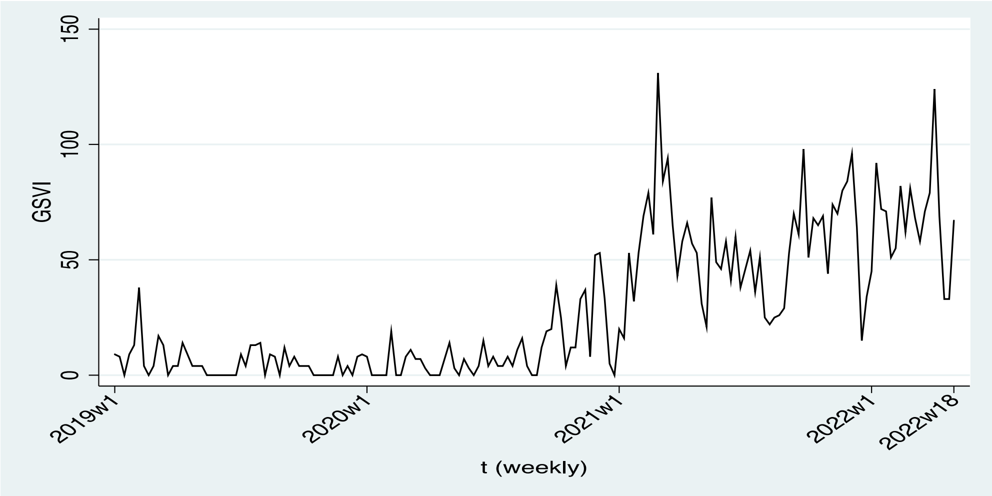

Fig. 1. SFDR-GSVI
Note(s): Fig. 1 shows the cumulative weekly searches of SFDR. The horizontal axis shows the weekly dates, and the vertical axis corresponds to weekly searches. Data is retrieved from Google Trends.

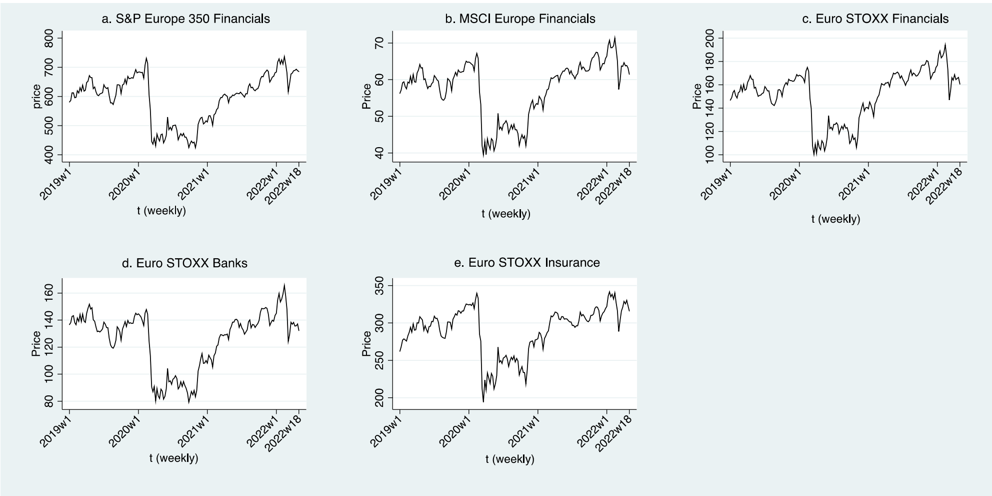

Fig. 2. Price series of European financial sector market indexes
Note(s): Fig. 2 shows the weekly prices of European financial sector equity market indexes from January 2019 to April 2022. The horizontal axis responds to weekly dates and the vertical axis corresponds to the price range. Data is from Bloomberg.

Financials, MSCI Europe Financials, and Euro STOXX Financials) and sub-indexes representative of single financial industries (namely, Euro STOXX Banks and Euro STOXX Insurance). Data were retrieved from Bloomberg. Fig. 2 shows price trends during the period of analysis.

3. Results and discussion

Table 1 shows the descriptive statistics of SFDR-GSVI and European financial sector market indexes. The SFDR-GSVI has a mean of 27.988, indicating the intensity of the search volume.

The skewness and kurtosis highlight that the data is non-symmetrical and non-normal. The Jarque-Bera test (JB) confirms the nonlinearity of our data and suggests using a nonparametric causality approach (Raza et al., 2022).

We tested the linearity of the relationship before applying the nonlinear causality-in-quantiles technique. The linear VAR (1) model was evaluated using the Granger causality test. Table 2 shows that the null hypothesis (i.e., SFDR-GSVI does not Granger cause European financial markets) is not rejected at all significance levels. Furthermore, to strengthen the argument that our data are nonlinear and nonparametric causality in quantiles technique is suitable for analysis, we applied the Broock et al. (1996) (BDS) Test of

Table 1
Descriptive statistics.

	Mean	SD	Kurtosis	Skewness	JB	ADF
SFDR-GSVI	27.988	30.126	0.118	0.994	28.3441***	-13.962***
S&P Europe 350 Financials	594.912	-0.779	2.198	-0.779	8.879***	16.653***
MSCI Europe Financials	57.78	-0.333	2.626	-0.333	18.616***	17.427***
Euro STOXX Financial	151.824	-0.277	2.98	-0.277	15.513***	17.749***
Euro STOXX Banks	125.855	-0.563	2.760	-0.77	18.015***	17.268***
Euro STOXX Insurance	290.013	0.065	3.009	0.065	21.568***	17.285***

Where $^{***}p < 0.001$.
Note: Standard deviation (SD), Jarque-Bera test (JB), and Augmented, Dickey and Fuller test (ADF). Data about stock prices are from Bloomberg, while SFDR-GSVI data is retrieved from Google Trends.

Table 2
Linear causality.

	F	p-value
S&P Europe 350 Financials	0.772	0.511
MSCI Europe Financial	0.6811	0.564
Euro STOXX Financials	0.8276	0.480
Euro STOXX Banks	0.553	0.648
Euro STOXX Insurance	0.5939	0.619

Note: The results confirm the acceptance of the null hypothesis i.e., no granger causality at the 5% level of significance.
Data about stock prices are from Bloomberg, while SFDR-GSVI data is retrieved from Google Trends.

Table 3
BDS Test of nonlinearity.

	$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$
SFDR-GSVI	2.454	3.561	5.303	8.509	4.449
S&P Europe 350 Financials	3.737	5.04	5.715	6.567	7.276
MSCI Europe Financials	4.745	5.55	5.81	6.654	6.775
Euro STOXX Financials	5.535	6.228	6.408	7.974	9.752
Euro STOXX Banks	4.245	6.1	6.77	8.398	7.868
Euro STOXX Insurance	6.927	7.525	7.697	8.959	9.87

Note(s): The table displays the BDS test z-statistics of all listed variables. The test is based on residuals of variables, "m" denotes the embedded dimensions of the test. The table also shows that BDS test values for all variables are significant at 1% level meaning the whole hypothesis is rejected, and all the variables are non-linear.
Data about stock prices are from Bloomberg, while SFDR-GSVI data is retrieved from Google trends.

nonlinearity. The BDS Test (Table 3) confirms the nonlinearity relationship between investor attention to SFDR and financial market prices.

Fig. 3 displays the nonparametric causality in quantiles from the SFDR-GSVI to European financial sector market indexes.

First, Fig. 3a presents the results of quantile causality between investor attention and S&P Europe 350 Financials. The result shows that the null hypothesis (i.e., SFDR-GSVI does not Granger cause European financial markets) is rejected for the middle quantile (0.45–0.65). Similarly, in the case of MSCI Europe Financials (Fig. 3b) and Euro STOXX Financials (Fig. 3c) the null hypothesis is rejected in the lower-middle quantile (0.3–0.65). Only STOXX Financials rejects the null hypothesis also at the upper quantile (0.7–0.75). The sensitivity of European financial markets to GSVI-SFDR is confirmed by results on the sub-sector indexes Euro STOXX Banks (Fig. 3d) and Euro STOXX Insurance (Fig. 3e).

Thus, European financial markets appear sensitive to investor attention to the SFDR, suggesting the price relevance of sustainability disclosure for financial market participants. The predictive power of investor attention is mostly a lower-middle quantile, so, investor attention to SFDR matters mostly when the European financial markets perform below or in line with their market average, thus, either in bearish or normal scenarios (Balcilar et al., 2017). This may be explained by the investors' pessimistic (optimistic) view during certain market conditions. Investors over-react (under-react) toward new compliance requirements during bearish (bullish) markets.

Overall, our findings expand the results by Becker et al. (2022) on the relationship between SFDR and mutual funds inflow/ESG scores, demonstrating that investor attention to SFDR is a predictor of equity financial prices.

To check the robustness of our results, first, we employ the nonparametric causality in quantiles technique on the daily Google Trends[5] and the daily prices of European financial markets. The daily results of either European financial indexes (Figs. 4a, 4b, and 4c)

[5] To retrieve daily Google Trend on SFDR we use R programming package "gtrendsR", based on Chow and Lin's (1971) disaggregation routine.

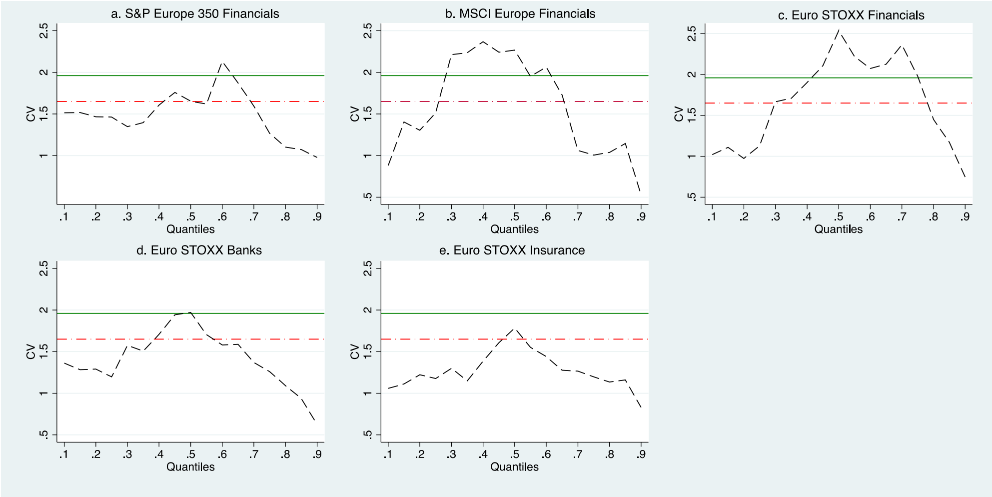

Fig. 3. Nonparametric causality in quantiles
Note(s): The test statistics of non-parametric causality are represented on the vertical axis and quantiles from 0.00 to 0.9 are on the horizontal axis. The dashed black line represents test statistics, where the red thin dashed and dotted line represents the 10% critical value (CV) of 1.65 and the green line represents 5% critical value (CV) of 1.96. Test statistic values between or above red thin dotted and dashed lines and green lines show rejection of the null hypothesis that SFDR-GSVI does not lead financial sector market prices. Data about stock prices are from Bloomberg, while SFDR-GSVI data is retrieved from Google Trends.

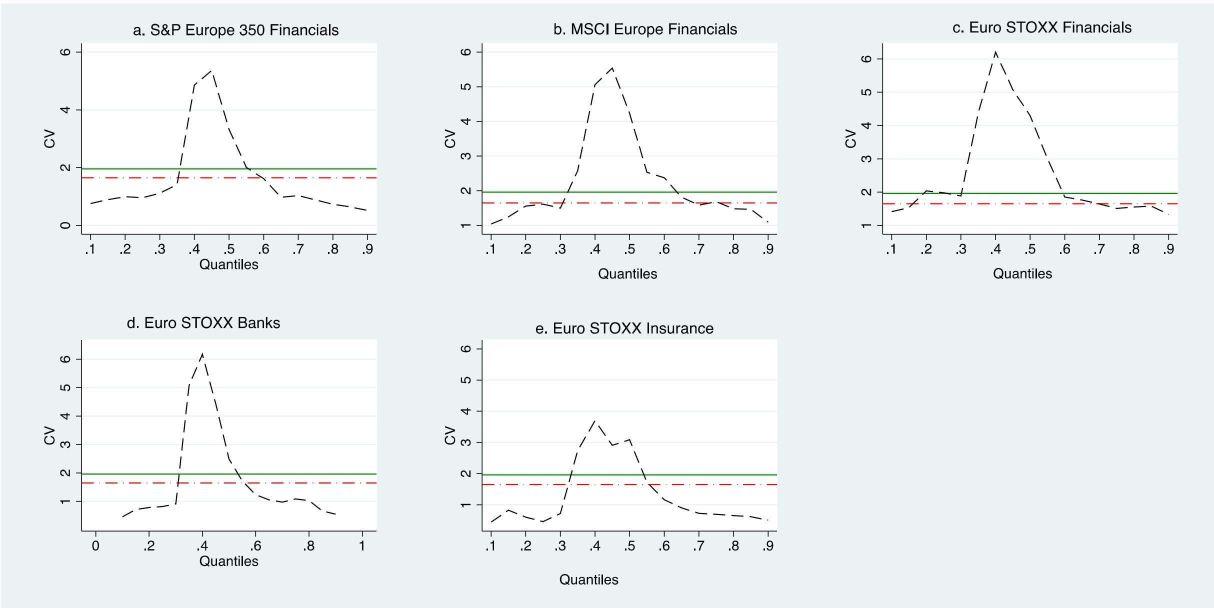

Fig. 4. Nonparametric causality in quantiles (Daily data series)
Note(s): The test statistics of non-parametric causality are represented on the vertical axis and quantiles from 0.00 to 0.9 are on the horizontal axis. The dashed black line represents test statistics, where the red thin dashed and dotted line represents the 10% critical value (CV) of 1.65 and the green line represents 5% critical value (CV) of 1.96. Test statistic values between or above red thin dotted and dashed lines and green lines show rejection of the null hypothesis that SFDR-GSVI does not lead financial sector market prices. Data about stock prices are from Bloomberg, while SFDR-GSVI data is retrieved from Google Trends.

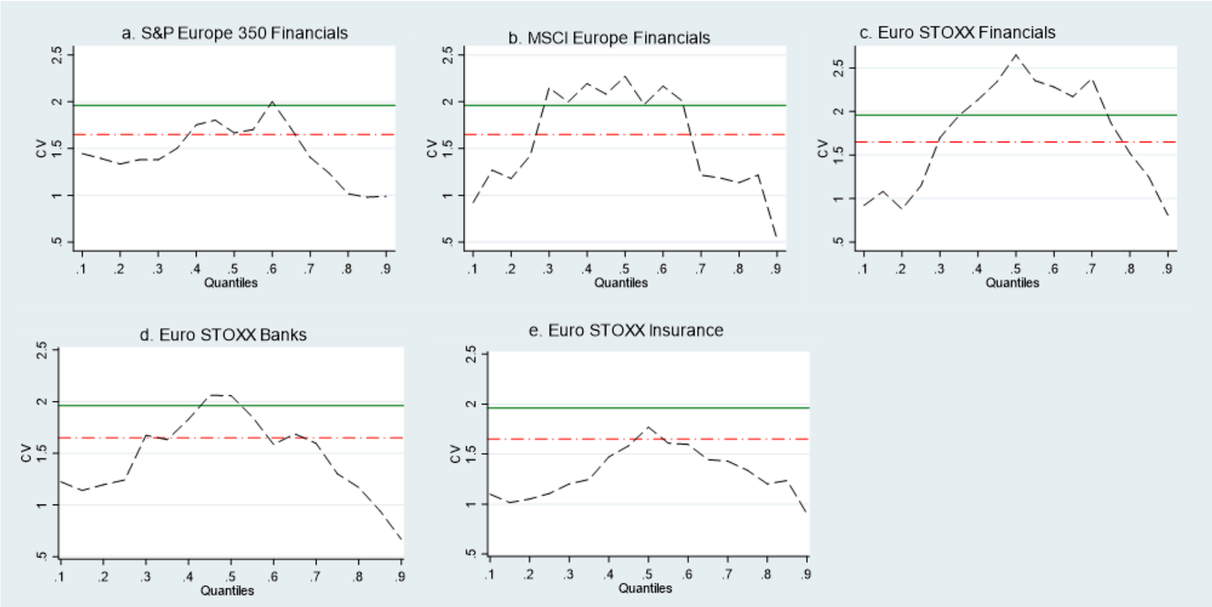

Fig. 5. Nonparametric causality in quantiles (weekly data with reduced SFDR keywords)
Note(s): The test statistics of non-parametric causality are represented on the vertical axis and quantiles from 0.00 to 0.9 are on the horizontal axis. The dashed black line represents test statistics, where the red thin dashed and dotted line represents the 10% critical value (CV) of 1.65 and the green line represents 5% critical value (CV) of 1.96. Test statistic values between or above red thin dotted and dashed lines and green lines show rejection of the null hypothesis that SFDR-GSVI does not lead financial sector market prices. Data about stock prices are from Bloomberg, while SFDR-GSVI data is retrieved from Google Trends.

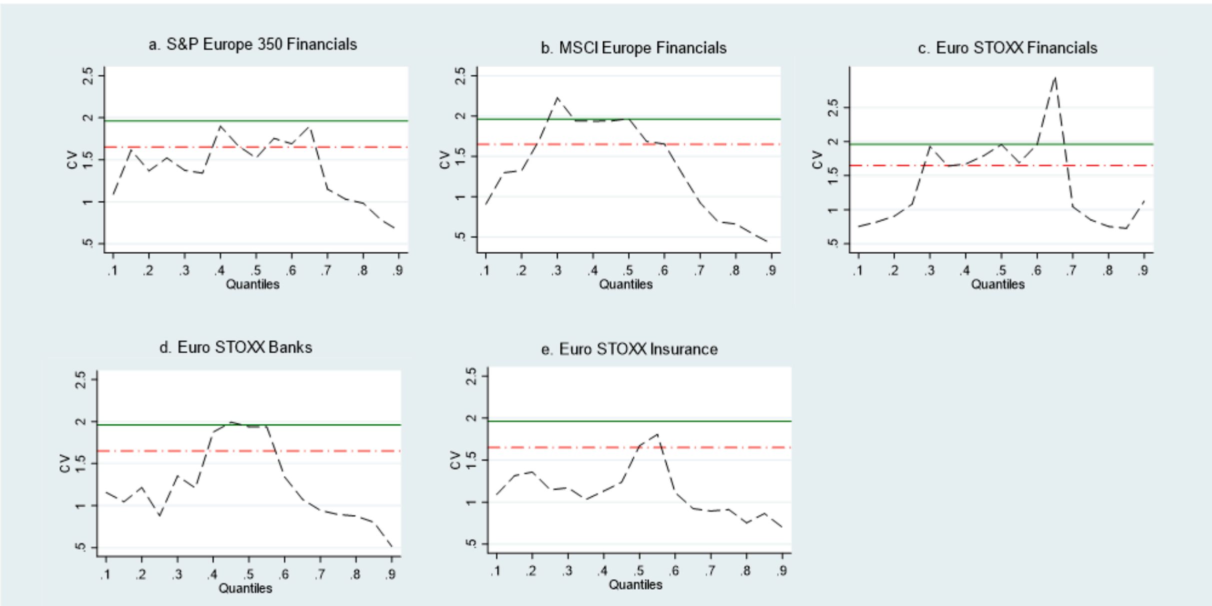

Fig. 6. Nonparametric causality in quantiles with seasonality robustness
Note(s): The test statistics of non-parametric causality are represented on the vertical axis and quantiles from 0.00 to 0.9 are on the horizontal axis. The dashed black line represents test statistics, where the red thin dashed and dotted line represents the 10% critical value (CV) of 1.65 and the green line represents 5% critical value (CV) of 1.96. Test statistic values between or above red thin dotted and dashed lines and green lines show rejection of the null hypothesis that SFDR-GSVI does not lead financial sector market prices. Data about stock prices are from Bloomberg, while SFDR-GSVI data is retrieved from Google Trends.

Fig. 7. Nonparametric causality in quantiles (Euro STOXX Ex-Financials)
Note(s): The test statistics of non-parametric causality are represented on the vertical axis and quantiles from 0.00 to 0.9 are on the horizontal axis. The dashed black line represents test statistics, where the red thin dashed and dotted line represents the 10% critical value (CV) of 1.65 and the green line represents 5% critical value (CV) of 1.96. Test statistic values between or above red thin dotted and dashed lines and green lines show rejection of the null hypothesis that SFDR-GSVI does not lead financial sector market prices. Data about stock prices are from Bloomberg, while SFDR-GSVI data is retrieved from Google Trends.

Table 4
Nonparametric granger causality test.

	$m = 2$	$m = 3$	$m = 4$
S&P Europe 350 Financials	2.37**	2.41**	2.51**
MSCI Europe Financials	2.67**	1.515*	1.495*
Euro STOXX Financials	1.786**	1.763**	1.964**
Euro STOXX Banks	2.245**	1.442*	1.526*
Euro STOXX Insurance	1.731**	1.852**	1.995**

Note(s): m denotes the embedding dimension.
** $p < 0.05$.
* 0.10 indicates the rejection of null hypothesis of no-causality.
Data about stock prices are from Bloomberg, while SFDR-GSVI data is retrieved from Google Trends.

and sub-industry indexes (Figs. 4d and 4e) confirm that investor attention to SFDR is a predictor for financial prices.

Second, we check the robustness of our findings using two different sets of keywords to identify the SFDR-GSVI[6] (Aslanidis et al., 2022; Scott and Varian, 2014). Figs. 5a, 5b, and 5c show the null hypothesis is rejected in lower-middle quantiles, confirming that SFDR-GSVI does lead European financial markets, while Fig. 5c shows that the null hypothesis is also rejected at upper quantile (0.7–0.75). Lastly, Figs. 5d and 5e confirm the presence of causality in quantiles in the sub-sector indexes. The results related to the single keyword "SFDR" also confirm the main findings.[7]

As a third robustness test, we control our results for week seasonality, following Reyes (2018). Prior studies indeed highlight the GSVI weekly data may have a strong day-of-the-week seasonality (Campos et al., 2017; Monaco and Murgia, 2023; Reyes, 2018). The robustness of seasonality confirms the presence of causality in quantiles (Fig. 6) validating our baseline results.

In addition, the nonparametric causality in quantiles on the alternative sample of Euro STOXX Ex-Financials reasonably confirms no causal relationship between investor attention to SFDR and non-financial market actors, either for weekly or daily estimation (Fig. 7a, 7b).

Finally, as a last battery of robustness checks, we employ nonparametric Granger causality test with embedding dimensions to

[6] The first alternative set includes the keywords "Sustainable Finance Disclosure Regulation", "SFDR", "SFDR Regulations", "SFDR sustainability", "SFDR ESG" (Figure 5), while in the second alternative set of keywords we consider only the keyword "SFDR".
[7] For reasons of brevity, results are available upon request.

analyze the nonlinear causal association between SFDR-GSVI and financial markets (Table 4). The findings reveal that the null hypothesis is rejected on all the embedding dimensions, supporting the validity of causality in quantiles technique.

4. Conclusion

Using a unique dataset and nonparametric causality in quantile, our study reveals that investor attention toward SFDR matters in European financial equity price prediction. The results are robust to daily analysis, alternative measures of GSVI, day-of-the-week seasonality robustness, alternative analysis on non-financial equity markets, and alternative model specifications.

First, our research offers novel insights into the stream of literature investigating the price relevance of investor attention toward specific events and the nascent literature on sustainable finance regulation. Second, our findings have important implications for asset managers and investors, suggesting the rebalancing of financial portfolios should consider investor attention toward sustainability disclosure. Furthermore, the sensitivity at lower-middle quantiles suggests that regulation may mostly affect financial markets when other negative conditions occur (e.g., geopolitical uncertainty or pandemic emergency).

Future research may expand the analysis of the link between investor attention and sustainable finance, by also considering other regulations and sustainable financial markets. Similarly, future research may investigate whether SFDR positively or negatively affects financial markets, since our research provides evidence of sensitivity, but not of the sign of the relationship, also over other exogenous events.

CRediT authorship contribution statement

Giuliana Birindelli: Conceptualization, Validation, Investigation, Writing – review & editing. **Helen Chiappini:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Raja Nabeel-Ud-Din Jalal:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft.

Data Availability

Data will be made available on request.

Acknowledgements

We are extremely thankful to the Editors, Guest Editors, two anonymous referees, Syed Ali Raza and participants at the "YSBC Sustainable and Socially Responsible Finance Conference" (Bologna, 6-7 October 2022) for their insightful comments and suggestions.

Appendix A

We used weekly SFDR-GSVI to empirically analyze the prediction power of investor attention on the European financial equity markets. The SFDR-GSVI are explained by "$\boldsymbol{y_t}$", and European equity index prices are explained by "$\boldsymbol{X_t}$". According to Jeong et al. (2012) the y_t ***does not lead*** X_t *in the* θ*-quantile, considering the lag-vectors of* $\{y_{t-1}, \ldots, y_{t-p}, X_{t-1}, \ldots, X_{t-p}\}$if:

$$Q\theta = y_t|y_{t-1}, \ldots, y_{t-p}, X_{t-1}, \ldots, X_{t-p}) = Q\theta\left(y_t y_{t-1}, \ldots, y_{t-p}\right) \tag{1}$$

In the θ-quantile X_t possibly cause y_t regarding$\{y_{t-1}, \ldots, y_{t-p}, X_{t-1}, \ldots, X_{t-p}\}$if:

$$Q\theta = y_t|y_{t-1}, \ldots, y_{t-p}, X_{t-1}, \ldots, X_{t-p}) \neq Q\theta\left(y_t y_{t-1}, \ldots, y_{t-p}\right) \tag{2}$$

In Eq. (2) $Q\theta = (y_t.)$ symbolizes θ-the quantile of$y_t$which is contingent on t, and the quantiles are bound among 0 or 1, i.e., $0 < \theta < 1$.

The $y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})$, $X_{t-1} \equiv (X_{t-1}, \ldots, X_{t-p})$, $Z_t = (X_t, y_t)$vectors are defined to explain the causality-in-quantiles test. Also, the conditional distribution, which is defined by $Fy_t|y_{t-1}$, $(y_t, |y_{t-1})$, $Fy_t|Z_{t-1}$, $(y_t, |Z_{t-1})$, signifies the distribution function y_t and is conditioned on vectors Z_{t-1} and y_{t-1} . $F_{yt}|Z_{t-1}$, $(y_t, |Z_{t-1})$ is supposed to be entirely continuous in y_t for all Z_{t-1}.

We can construct $Fy_t|tZ_{t-1}\{Q\theta(Z_{t-1})|Z_{t-1}\} = \theta$ having a probability of 1 by denoting $Q\theta(Z_{t-1}) \equiv Q\theta(y_t|Z_{t-1})$, and $Q\theta(y_{t-1}) \equiv Q\theta(y_t|y_{t-1})$. Thus, the hypotheses that need to be tested based on Eqs. (1) and 2 are given below.

$$H_0 : P\ \{Fy_t|Z_{t-1}\{Q\theta(y_{t-1})|\ Z_{t-1}\} = \theta\} = 1 \tag{3}$$

$$H_1 : P\ \{Fy_t|Z_{t-1}\{Q\theta(y_{t-1})|\ Z_{t-1}\} = \theta\} < 1 \tag{4}$$

Also, Jeong et al. (2012) used $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1})F_z|Z_{t-1})\}$to measure the distance, where ε_t displays the error and function of marginal density as represented by$F_z(Z_{t-1})$. The null hypothesis in Eq. (3) will be held as correct if $E[1\{y_t \leq Q\theta(y_{t-1})Z_{t-1}\} = \theta]$or $1\{y_t \leq Q(y_{t-1})\}] = \theta + \varepsilon_t$, where $1\{\cdot\}$ is the indicator function and the Jeong et al. (2012) function is

$$J = E\left[\left\{Fy_{t|Z_{t-1}}\{Q\theta(y_{t-1})|Z_{t-1}\}\ - \theta\right\}^2 \mathrm{F_z}(\mathrm{Z}_{t-1})\right] \tag{5}$$

A feasible kernel-based causality in quantiles test statistics for fixed θ-quantile can be represented as

$$\widehat{J_T} = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s \neq P+1}^{T} s \neq t \; K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \widehat{\varepsilon}_t \widehat{\varepsilon}_s \tag{6}$$

Where “h” is bandwidth, t is the sample size, kernel function (.) and the lag order (p) is determined by Schwarz criterion (SIC). The unknown regression error is represented by $\widehat{\varepsilon}_t$ and is calculated by;

$$\widehat{\varepsilon_t} = 1\{y_t \leq \widehat{Q}\theta(y_{t-1})\} - \theta, \tag{7}$$

where $\widehat{Q}\theta(y_{t-1})$ calculates the θ-th conditional quantile of y_t of y_{t-1} and $\widehat{Q}\theta(y_{t-1})$ is calculated through a nonparametric kernel approach as given below.

$$\widehat{Q}\theta(y_{t-1}) = \widehat{F}^{-1}_{yt|y_{t-1}}(\theta y_{t-1}) \tag{8}$$

$\widehat{F}_{yt|yt-1}(y_t y_{t-1})$ is described as

$$\widehat{F}_{yt|yt-1}(y_t y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{y_{t-1} - y_{s-1}}{h}\right) 1\,(y_s \leq y_t)}{\sum_{s=p+1,\; s\neq t}^{T} L\left(\frac{y_{t-1} - y_{s-1}}{h}\right)} \tag{9}$$

Where L (.) is the Kernel function and h is the bandwidth based on gaussian kernels and least square cross-validation technique.

Also, based on Jeong et al. (2012) and Nishiyama et al.’s (2011) work, Balcilar et al. (2017) developed high order moment causality in quantiles as mentioned below;

$$H_0 : P\left\{Fy_t^k | Z_{t-1}\{Q\theta(y_{t-1}) |\, Z_{t-1}\} = \theta\right\} = 1, \; for\; k = 1, 2, \; 3, \ldots K \tag{10}$$

$$H_1 : P\left\{Fy_t^k | Z_{t-1}\{Q\theta(y_{t-1}) |\, Z_{t-1}\} = \theta\right\} < 1, \; for\; k = 1, 2, \; 3, \ldots K \tag{11}$$

which summarize into y_t ***does lead*** X_t *in the θ-quantile*.

Using Eq. (10), we constructed the test statistic value of each k in Eq. (6) (Raza et al., 2022) using the sequential testing method, which resolves the equal correlation issue of different test statistics.

References

Anastasiou, D., Kallandranis, C., Drakos, K., 2022. Borrower discouragement prevalence for Eurozone SMEs: investigating the impact of economic sentiment. J. Econ. Behav. Organ. 194, 161–171. https://doi.org/10.1016/j.jebo.2021.12.022.

Aslanidis, N., Bariviera, A.F., López, Ó.G., 2022. The link between cryptocurrencies and Google trends attention. Financ. Res. Lett., 102654 https://doi.org/10.1016/j.frl.2021.102654.

Austmann, L.M., Vigne, S.A., 2021. Does environmental awareness fuel the electric vehicle market? A Twitter keyword analysis. Energy Econ. 101, 105337 https://doi.org/10.1016/j.eneco.2021.105337.

Balcilar, M., Bekiros, S., Gupta, R., 2017. The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method. Empir. Econ. 53 (3), 879–889. https://doi.org/10.1007/s00181-016-1150-0.

Barber, B.M., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Rev. Financ. Stud. 21 (2), 785–818. https://doi.org/10.1093/rfs/hhm079.

Becker, M.G., Martin, F., Walter, A., 2022. The power of ESG transparency: the effect of the new SFDR sustainability labels on mutual funds and individual investors. Financ. Res. Lett. https://doi.org/10.1016/j.frl.2022.102708.

Bhatia, V., Basu, S., 2021. Causality-in-quantiles between crude oil and stock markets: evidence from emerging economies. Financ. Res. Lett. 40, 101736 https://doi.org/10.1016/j.frl.2020.101736.

Bonaparte, Y., Bernile, G., 2023. A new “Wall street darling?” effects of regulation sentiment in cryptocurrency markets. Financ. Res. Lett. 52, 103376 https://doi.org/10.1016/j.frl.2022.103376.

Broock, W.A., Scheinkman, J.A., Dechert, W.D., LeBaron, B., 1996. A test for independence based on the correlation dimension. Econom. Rev. 15 (3), 197–235. https://doi.org/10.1080/07474939608800353.

Campos, I., Cortazar, G., Reyes, T., 2017. Modeling and predicting oil VIX: internet search volume versus traditional mariables. Energy Econ. 66, 194–204. https://doi.org/10.1016/j.eneco.2017.06.009.

Chow, G.C., Lin, A., 1971. Best linear unbiased interpolation, distribution, and extrapolation of time series by related series. Rev. Econ. Stat. 53 (4) https://doi.org/10.2307/1928739, 372–37.

Corbet, S., Larkin, C., Lucey, B., Yarovaya, L., 2020. KODAKCoin: a blockchain revolution or exploiting a potential cryptocurrency bubble? Appl. Econ. Lett. 27 (7), 518–524. https://doi.org/10.1080/13504851.2019.1637512.

Costola, M., Iacopini, M., Santagiustina, C.R., 2021. Google search volumes and the financial markets during the COVID-19 outbreak. Financ. Res. Lett. 42, 101884 https://doi.org/10.1016/j.frl.2020.101884.

Cremasco, C., Boni, L., 2022. Is the European union (EU) sustainable finance disclosure regulation (SFDR) effective in shaping sustainability objectives? An analysis of investment funds’ behaviour. J. Sustain. Financ. Investment 1–19. https://doi.org/10.1080/20430795.2022.2124838.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. J. Financ. 66 (5), 1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x.

Dastgir, S., Demir, E., Downing, G., Gozgor, G., Lau, C.K.M., 2019. The causal relationship between Bitcoin attention and Bitcoin returns: evidence from the Copula-based Granger causality test. Financ. Res. Lett. 28, 160–164. https://doi.org/10.1016/j.frl.2018.04.019.

Dergiades, T., Milas, C., Panagiotidis, T., 2015. Tweets, Google trends, and sovereign spreads in the GIIPS. Oxf. Econ. Pap. 67 (2), 406–432. https://doi.org/10.1093/oep/gpu046.

Gao, Y., Li, Y., Wang, Y., 2021. The dynamic interaction between investor attention and green security market: an empirical study based on Baidu index. China Financ. Rev. Int. https://doi.org/10.1108/CFRI-06-2021-0136.

González-Fernández, M., González-Velasco, C., 2020. An alternative approach to predicting bank credit risk in Europe with Google data. Financ. Res. Lett. 35, 101281 https://doi.org/10.1016/j.frl.2019.08.029.

Halousková, M., Stašek, D., Horváth, M., 2022. The role of investor attention in global asset price variation during the invasion of Ukraine. Financ. Res. Lett. 50, 103292 https://doi.org/10.1016/j.frl.2022.103292.

Jeong, K., Härdle, W.K., Song, S., 2012. A consistent nonparametric test for causality in quantile. Econ. Theory 28 (4), 861–887. https://doi.org/10.1017/S0266466611000685.

Jun, S.P., Sung, T.E., Park, H.W., 2017. Forecasting by analogy using the web search traffic. Technol. Forecast. Soc. Change 115, 37–51. https://doi.org/10.1016/j.techfore.2016.09.014.

Monaco, E., Murgia, L.M., 2023. Retail attention and the FOMC equity premium. Financ. Res. Lett. 53, 103597 https://doi.org/10.1016/j.frl.2022.103597.

Raza, S.A., Ahmed, M., Aloui, C., 2022a. On the asymmetrical connectedness between cryptocurrencies and foreign exchange markets: evidence from the nonparametric quantile on quantile approach. Res. Int. Bus. Financ. 61, 101627 https://doi.org/10.1016/j.ribaf.2022.101627.

Raza, S.A., Yarovaya, L., Guesmi, K., Shah, N., 2022b. Google Trends and cryptocurrencies: a nonparametric causality-in-quantiles analysis. Int. J. Emerg. Mark. https://doi.org/10.1108/IJOEM-10-2021-1522. Vol. ahead-of-print No. ahead-of-print.

Reyes, T., 2018. Limited attention and M&A announcements. J. Empirical Financ. 49, 201–222. https://doi.org/10.1016/j.jempfin.2018.10.001.

Scott, S.L., Varian, H.R., 2014. Predicting the present with Bayesian structural time series. Int. J. Mathematical Modell. Numerical Optimisation 5 (1–2), 4–23. https://doi.org/10.1504/IJMMNO.2014.059942.

Wei, H., Guo, Y., Yu, Z., Cheng, H., 2021. The impact of events on metal futures based on the perspective of Google trends. Resour. Policy 74, 102286. https://doi.org/10.1016/j.resourpol.2021.102286.