Regulating Greenwashing: Spillover Effects of Sustainable Financial Disclosure Regulation

By

Congyang Ding

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Preceptor: Sergio Salas

Abstract

This paper[1] investigates the spillover effects of Sustainable Financial Disclosure Regulation(SFDR) in reducing greenwashing. To quantify greenwashing, the paper employs a pre-trained NLP model called FinBERT to analyze public statements by companies. Using a Difference-in-Differences (DiD) approach, the paper finds that SFDR can effectively reduce greenwashing not only in the financial sector but also in non-financial sectors. The paper then presents theoretical models to understand the channels through which SFDR influences the non-financial sector. Finally, the paper tests the theoretical models by utilizing the eligibility to SFDR as an IV and establishing a causal relationship between the greenwashing risk in different sectors.

Keywords: Greenwashing, Spillover, ESG, Sustainable Finance, FinBERT

[1]E-mail address: congyang@uchicago.edu

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1 Introduction

In recent years, people are increasingly concerned about environmental, social, and governance (ESG) issues, and this awareness is shaping their purchasing and investment decisions. While this trend toward sustainability is certainly a positive development, it has also led to a surge in greenwashing practices, where market participants make misleading or exaggerated claims about their ESG properties and the environmental benefits of their products or services. Greenwashing not only misleads consumers into purchasing products that are not as environmentally friendly as advertised, but also diverts attention and resources away from genuinely sustainable solutions.

To address the problem of greenwashing and ensure the credibility of ESG information disclosure, regulatory measures are necessary. One such regulation is the Sustainable Finance Disclosure Regulation (SFDR) in the EU, which mandates financial institutions to disclose how they integrate ESG factors into their financial products. Unlike voluntary initiatives like the EU Non-Financial Reporting Directive, Task Force on Climate-related Financial Disclosures (TCFD) recommendations, Global Reporting Initiative (GRI), and Carbon Disclosure Project (CDP), SFDR imposes mandatory binding obligations for specific ESG disclosures in the EU. This unique enforcement power of SFDR makes it easier for us to draw general conclusions about its effectiveness.

The primary objective of SFDR is to increase transparency and reduce greenwashing in the financial sector. However, are there any potential spillover effects of SFDR that may influence the non-financial sector as well? This paper aims to investigate this problem. To provide a way of quantifying greenwashing, this paper uses a pre-trained Natural Language Processing (NLP) model called FinBERT to analyze the public statements of companies. Employing a Difference-in-Differences (DiD) approach, the paper then shows that SFDR can effectively reduce greenwashing not only in the financial sector but also in non-financial public firms that are not directly subject to SFDR regulation. Specifically, it can effectively reduce greenwashing of the companies that could be selected by ESG funds(Green Public Firms). Spillover from the EU(where SFDR is employed) to other regions is also analyzed, the result shows that the impact of the SFDR on greenwashing is not statistically significant for neighboring countries of the EU.

To investigate the specific channels through which SFDR influences the non-financial sector, the paper first presents an empirical analysis and argues that SFDR can effectively enhance the true ESG performance of public green firms, while it has no significant effect on their ESG marketing efforts. This argument is supported by a theoretical model based on an extension of the sustainable investment equilibrium model of Pástor et al. (2021). Furthermore, the paper proposes a possible theoretical explanation for the non-significant impact of SFDR on the ESG marketing effort. Finally, the paper uses the eligibility to SFDR as an instrumental variable to test the theorem. This approach enables the paper to address potential endogeneity problems and establish a causal relationship between the greenwashing risk in the financial sector and the non-financial sector.

In all, by analyzing the spillover effects of SFDR and the influence mechanism, the paper aims to provide insights into the effectiveness of SFDR in regulating greenwashing in finance and the broader economy.

2 Background

In this section, we will begin by introducing the context of the study, followed by a review of prior researches related to greenwashing. We will then discuss the Sustainable Financial Disclosure Regulation (SFDR).

2.1 Context of the Study

In recent years, consumers have become more environmentally conscious and are actively seeking out products and services that align with these values. However, not all companies are genuine in their claims of environmental responsibility and some may use greenwashing tactics to deceive consumers and increase profits.

Greenwashing presents a significant challenge in the non-financial sector, as companies may exploit ESG initiatives for marketing purposes without genuinely implementing environmentally responsible practices across their supply chains. Nestlé[2], for instance, faced criticism for its vague eco-friendly packaging goals, which led to allegations of greenwashing from environmental organizations. Similarly, Coca-Cola and PepsiCo, despite their sustainability marketing efforts, were identified as the world's leading plastic polluters for three consecutive years. The fast fashion industry also demonstrates the prevalence of greenwashing, with brands labeling their clothing lines as 'sustainable' or 'ethical,' even though the sector is a major contributor to pollution and landfill waste. H&M's[3] "Conscious" collection faced scrutiny for potentially misleading environmental claims, and Zara's[4] "Join Life" collection, which purports to use sustainable materials, has been criticized as well. In the automobile industry, Volkswagen's[5] emissions scandal serves as a cautionary tale. The company falsely promoted its vehicles as eco-friendly while secretly cheating on emissions tests. This deception not only misled consumers but also caused significant environmental and public health damage, as the engines emitted up to 40 times the permitted levels of nitrogen oxide pollutants.

[2]See https://www.ecowatch.com/nestle-plastic-pollution-greenpeace-2558963533.html

[3]For details, see https://www.brandingmag.com/2019/12/12/hms-greenwashing-short-sighted-and-unethical/

[4]See https://www.euronews.com/green/2022/06/26/clothes-made-from-carbon-emissions-why-zaras-new-line-is-just-more-greenwashing

[5]For details, see https://www.jru.university/post/volkswagen-emissions-scandal-forty-years-of-greenwashing-the-well-travelled-road-taken-by-vw

Greenwashing could also be an urgent issue in the financial sector. HSBC[6], for instance, has faced accusations of greenwashing due to its ongoing support for coal projects, even after committing to carbon neutrality. In today's market, financial market participants increasingly prioritize green and sustainable investments to address climate change. However, a study by Raghunandan and Rajgopal (2022) revealed that ESG mutual funds in the US often invest in companies with poorer compliance records regarding labor and environmental laws compared to non-ESG funds managed by the same institutions. This finding underscores the need for greater transparency and accuracy in assessing the environmental and social impacts of investments, as well as the importance of avoiding greenwashing in the financial sector.

Greenwashing becomes an increasingly urgent problem, prompting governments and organizations to recognize the need for clear regulations and guidelines to mitigate deceptive marketing practices. The UK's Advertising Standards Authority, for instance, has enforced more stringent guidelines for businesses making environmental claims in their advertisements. Similarly, the Canadian government has adopted a labeling system for biodegradable products to ensure accurate information. Moreover, the Australian Competition and Consumer Commission has pursued legal action against companies for making false or misleading environmental claims, demonstrating a commitment to combating greenwashing. The International Organization for Standardization has also contributed to this effort by developing a range of environmental management standards, such as ISO 14001, which offers guidance for implementing effective environmental management systems. These combined efforts help to promote transparency, accuracy, and accountability in environmental marketing and business practices.

[6]See https://fortune.com/2022/10/19/hsbc-slapped-running-ads-saying-green-when-not-uk-cap-code-asa/

Some actions in the financial sector are also put in place. The Equator Principles, for example, offers a framework for banks to manage social and environmental risks in project financing. Additionally, the U.S. Securities and Exchange Commission (SEC)[7] has approved proposals to enhance scrutiny of ESG funds and advisers' ESG practices. The Climate Bonds Initiative has introduced a certification scheme for bonds financing projects with positive environmental impacts. Furthermore, the Carbon Disclosure Project encourages companies to disclose their greenhouse gas emissions and climate-related risks and opportunities. However, most of these actions are only voluntary initiatives, which makes it difficult for us to draw a general conclusion about their effectiveness. In contrast, the European Union's Sustainable Finance Disclosure Regulation (SFDR) is mandatory. The SFDR requires financial market participants to disclose information about the environmental and social impact of their investment products. Studying the SFDR is essential, because it offers valuable insights into effective ESG disclosure practices and serves as a benchmark for other regions in developing their own regulatory frameworks. Therefore, this paper aims to study the effectiveness of the SFDR in reducing greenwashing in the financial sector and its spillover effects on non-financial sectors. By analyzing the SFDR's impact on regulating greenwashing, this study seeks to contribute to a more comprehensive understanding of the effectiveness of mandatory financial regulations and guidelines in promoting sustainable and transparent business practices.

2.2 Prior Studies related to Greenwashing

The literature on greenwashing remains limited, primarily due to the challenges in differentiating authentic ESG commitments from deceptive ones, as well as the absence of standardized metrics and transparency in ESG reporting. Empirical study of greenwashing

[7] For details, see https://www.sec.gov/sec-response-climate-and-esg-risks-and-opportunities

proves particularly difficult, given the complexities in measuring and comparing the effectiveness of ESG practices across firms and funds. Despite these obstacles, recent studies have provided valuable insights into this issue.

Kim and Yoon (2023) conducted a study on the implementation of ESG practices by active US mutual funds that signed the UN Principles for Responsible Investment (PRI). They found that while these funds attracted significant inflows, there was no improvement in ESG scores or returns. To evaluate ESG incorporation, the authors compared fund-quarter level value-weighted average ESG scores in the six quarters before and after signing the PRI. The results suggest a potential presence of greenwashing among PRI funds, as there was limited evidence of genuine ESG incorporation in their investment decisions.

Heath et al. (2023) investigated the real effect of socially responsible investment (SRI) funds. They found that SRI funds primarily function as stock selectors and do not significantly influence the ESG conduct of their portfolio firms, even though they select firms with superior environmental and social performance. The authors suggest that SRI fund managers have limited incentives to invest in costly efforts to improve firm behavior, as fund flows are influenced by third-party rating agencies that prioritize stock selection over engagement. The study argues that SRI funds are engaged in impact-washing rather than greenwashing, as they fail to increase firms' environmental performance. This distinction is important, as it underscores the need for further research to understand why sustainable finance does not work as expected in driving real ESG performance improvement.

In contrast, Dyck et al. (2019) found a positive relationship between responsible investing and firm-level ESG performance using data from 41 countries. They observed that higher ownership by PRI signatories is associated with better E&S scores. The study suggests that investors drive firms' E&S performance worldwide and transplant their local social norms in the process. This finding highlights the potential of responsible investing to improve ESG performance and emphasizes the need for further research to ensure more consistent results across the sustainable finance landscape.

On the other hand, employing a comparative analysis of reported ESG incorporation and actual portfolio ESG scores,Gibson Brandon et al. (2022) demonstrate that non-US institutional investors signing the Principles for Responsible Investment (PRI) exhibit improved portfolio-level ESG scores compared to non-signatories. However, the paper shows that US exhibits a significant gap between investor claims and actual practices when it comes to ESG investing. This difference is attributed to factors such as higher financial incentives for US PRI signatories, regulatory ambiguity, and less mature ESG markets.

In conclusion, the literature on greenwashing reveals mixed findings, highlighting the complexities and inconsistencies in ESG implementation and reporting across firms and funds. Some studies, such as Kim and Yoon (2023) and Gibson Brandon et al. (2022), suggest potential greenwashing among PRI funds, while Heath et al. (2023) introduces the concept of impact-washing among SRI funds, arguing that the SRI funds fail to increase portfolio firms' real ESG performance. In contrast, Dyck et al. (2019) demonstrates a positive relationship between responsible investing and firms' ESG performance. These discrepancies emphasize the need for further research to better understand the factors driving the varying effectiveness of the sustainable finance practices.

In light of these findings, this paper seeks to bridge the gap in the literature by examining the effectiveness of the SFDR in mitigating greenwashing across both financial and non-financial sectors. Additionally, it seeks to explore the causal relationship between greenwashing in financial sectors and non-financial sectors, which provides a possible explanation for the observed discrepancies in the literature. By addressing these research needs, the study hopes to contribute to a more comprehensive understanding of greenwashing and its effects, as well as inform the development of more effective policies and regulations to promote genuine ESG improvements and sustainable finance practices.

2.3 Sustainable Financial Disclosure Regulation (SFDR)

The EU Sustainable Finance Disclosure Regulation (SFDR)[8] is a crucial component of the European Union's strategy to advance sustainable finance and mitigate greenwashing. Implemented on March 10, 2021, the SFDR aims to enhance transparency, standardization, and comparability in the sustainable investing sector.

The SFDR applies to various financial market participants and advisers, encompassing a range of financial products and services, such as Alternative Investment Funds(AIFs), separately-managed portfolios, sub-advisory mandates, and financial advice. The regulation affects activities within the EU and those provided by EU investment firms. Under SFDR, market participants and advisers must disclose their approach to Sustainability Risks and Principal Adverse Impacts. Sustainability Risks pertain to ESG events with potential negative impacts on investment value. In contrast, Principal Adverse Impacts refer to investment decisions' negative effects on sustainability factors, including carbon emissions and resource management practices.

By requiring comprehensive and consistent disclosures, the SFDR helps prevent greenwashing and enables investors to better evaluate sustainable investment options. Examining its impact is key to understanding how regulatory frameworks can foster genuine ESG improvements and enhance transparency in the broader economy.

[8] For details, see https://finance.ec.europa.eu/regulation-and-supervision/financial-services-legislation/implementing-and-delegated-acts/sustainable-finance-disclosures-regulation_en

3 Data and Sample

The sample period for this study ranges from 2019 Q3 to 2022 Q4, which covers a crucial time frame before and after the implementation of the SFDR at the end of 2021 Q1. This period allows for a comprehensive evaluation of the impact of the SFDR and captures changes in ESG practices and marketing efforts by companies and funds.

The non-financial sector company data was initially sourced from the RepRisk Standard Dataset, which was chosen over other ESG rating dataset due to its extensive coverage and methodological approach. RepRisk Standard Dataset offers information on approximately 20,000 listed companies exposed to ESG risks and business conduct issues across various sectors and geographies. As a provider of ESG risk research and quantitative solutions, RepRisk combines AI, machine learning, and human intelligence to systematically flag and monitor material ESG risks and violations of international standards. Its daily-updated data, synthesized in 23 languages, ensures up-to-date and accurate information, making RepRisk a suitable data source for this study.

From the RepRisk dataset, the quarterly average RepRisk Reputation Risk Index (RRI)[9], which measures the ESG risk exposure, was calculated for each company, resulting in a sample of 23,382 companies. The sample was then narrowed down to 2,861 companies with headquarters in the European Union (EU) to focus on the region where the SFDR is enforced. These companies' ISINs were used as identifiers to download corresponding fundamental data from the Eikon Refinitiv database, a reputable source for comprehensive financial data. The downloaded data includes Total Debt, Cash Flow, Total Assets, Pretax ROA, EBITDA, Cash and Short Term Investments, and Company Market Capital, serving as control variables for subsequent analyses.

[9] For more details, see https://www.reprisk.com/news-research/resources/methodology#a-what-is-the-reprisk-index-rri.

After removing missing values, the sample consisted of 1,141 companies. The Twitter accounts of these companies were manually searched, and their URLs collected. The choice to use Twitter data is based on the platform's popularity and accessibility for both companies and users, allowing for real-time communication and promotion of ESG practices. However, 384 companies did not have Twitter accounts, 50 had joined Twitter late or had inactive accounts, 11 had multiple accounts or branches, and 287 used languages other than English, 1's Twitter is for its football club information. These companies were removed from the sample. For the remaining 408 companies, all tweets, replies, and retweets were crawled to obtain textual data. The data was separated by sentences, and the BERT model was used to calculate the average ESG marketing effort for each quarter. This constitutes the non-financial company sample. The sample selection procedure is presented in Table 1 and the descriptive statistics are presented in Table 2.

For the financial sector, the Morningstar database was used to gather data on funds. This database was selected because of its extensive coverage of investment funds and its reliable indicators related to ESG practices. Also, Morningstar provides Sustainable Rating for Funds[10], which serves as a valuable metric for assessing the ESG performance of funds. ESG funds were selected based on the "sustainable investment" indicator[11] from Morningstar, which required a consistent "yes" rating from January 2019 to December 2022, resulting in a total of 1,865 funds. The main variables downloaded were FundId, Name, Base Currency, Investment Area, Domicile, Region of Sale, Fund Size, Beta 3 Year, Standard Deviation, Sharpe Ratio 3 Year, monthly return, monthly sustainable rating for funds, and monthly net asset per share.

[10] For details, see https://www.morningstar.com/articles/745796/introducing-the-morningstar-sustainability-rating-for-funds

[11] The paper uses the indicator of "sustainable investment" from Morningstar, which is "yes" if, in the prospectus or other regulatory lings of the fund, it is described as focusing on sustainability, impact investing, or environmental, social or governance factors. Funds must claim to have a sustainability objective, and/or use binding ESG criteria for their investment selection.

Table 1: Sample Selection for Non-Financial Sector Data

Description	**Net Companies**	**Remaining**
Initial RepRisk dataset	23,382	
Narrowed to EU-based companies	-20,521	2,861
Removed missing values	-1,720	1,141
Companies without Twitter accounts	-384	757
Joined Twitter late or inactive accounts	-50	707
Companies with multiple accounts	-11	696
Football club	-1	695
Non-English language accounts	-287	408
Final non-financial company sample		408

Table 2: Descriptive Statistics for Non-Financial Sector Data

Variable	N	Mean	SD	Min	p25	p50	p75	Max
greenwashing	4080	0.132	0.146	0	0	0.104	0.218	0.658
RRI	4080	12.80	13.08	0	0	12.12	21.79	53.09
esg mkt	4080	0.328	0.108	0.141	0.245	0.317	0.397	0.630
ln(total debt)	4080	20.21	3.741	0	19.12	20.91	22.24	25.11
ln(cash flow)	4080	17.41	6.901	0	17.70	19.84	21.04	23.94
ln(total asset)	4080	22.12	2.212	15.76	20.93	22.35	23.59	26.18
pretax roa	4080	0.0410	0.129	-0.539	0.0120	0.0530	0.0950	0.336
ln(ebitda)	4080	18.18	6.351	0	18.56	20.16	21.37	24.07
ln(cash shorn)	4080	19.80	2.244	12.57	18.59	20.03	21.25	23.90
ln(market cap)	4080	21.74	2.276	15.12	20.34	21.98	23.38	26.15

Note: Sample Period: 2019 Q3 - 2022 Q4; Sample Size: 408 Companies. Missing values generated after taking logarithms were replaced with 0 to maintain the original sample size and avoid potential biases. This approach is taken because the original values before taking the logarithm were extremely small or close to 0, representing minimal or negligible levels of the respective variable. Alternative imputation methods should also be considered when it is not the case.

Then, corresponding variables' quarterly averages and quarterly returns were calculated, and the funds' data was transformed into a balanced panel format. This completed the data processing, allowing for subsequent analysis. The descriptive statistics are shown in Table 3.

Table 3: Descriptive Statistics for Financial Sector Data

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Greenwashing	18650	0.0720	0.0830	0	0	0.0620	0.0910	0.375
ln(Fund Size)	18650	20.130	1.603	16.470	19.040	20.180	21.310	24.040
Beta	18650	0.988	0.142	0.523	0.917	0.990	1.054	1.514
Stand Deviation	18650	18.850	3.750	8.702	16.820	19.320	21.430	28.630
Sharpe Ratio	18650	0.630	0.341	-0.360	0.516	0.725	0.851	1.282
ln(Net Assets)	18650	16.580	2.959	7.034	15.110	17.080	18.700	21.520
Quarterly Return	18650	4.223	10.290	-25.060	-0.573	5.338	10.080	25.190

Note: Sample Period: 2019 Q3 - 2022 Q4; Sample Size: 1,865 Funds.

4 Identification of the Greenwashing Risk

In this section, we outline how we identify and measure the greenwashing risk of the financial sectors and non-financial sectors, and show the identification results.

While greenwashing has gained significant attention in recent years, there is a notable lack of literature specifically dedicated to this topic. Researchers investigating greenwashing face various challenges, including the intricate nature of the ESG topics and the scarcity of information regarding companies' actual practices. This lack of information makes it difficult to quantify greenwashing accurately. To address this issue, the paper proposes an original method for the identification and analysis of the greenwashing risk, aiming to provide a more objective and data-driven approach in studying ESG topics.

Greenwashing refers to making false or exaggerated claims about a product, service, or company's ESG benefits to attract environmentally conscious consumers (Delmas and Burbano, 2011). Such claims involve overstating the environmental impact of a product or service, making misleading statements about sustainability, or making vague and unsubstantiated claims about a company's commitment to sustainability, which shows a mismatch between the ESG marketing efforts and the real ESG performance. As such, the fundamental principle guiding our greenwashing risk measurement in this paper is to determine a greenwashing risk score based on the proportion of a company's ESG marketing frequency relative to its actual ESG performance. This approach aims to assess the authenticity of a company's environmental claims by comparing its marketing efforts to its actual environmental impact. By identifying the divergence between what is communicated and the company's real performance, we can better understand the degree of sincerity in their ESG commitment. The higher the greenwashing risk score, the greater the risk of a company engaging in greenwashing practices.

Recognizing that the financial sector may have a less direct impact on the environment compared to non-financial firms, the paper proposes different methods for measuring greenwashing in the financial and non-financial sectors. By tailoring the criteria used to measure greenwashing to the specific nature and characteristics of the sector where a company operates, a more accurate and nuanced assessment of greenwashing is obtained. The identification strategies are introduced separately in the following two sections.

4.1 Greenwashing Risk Score in the Non-financial Sector

To effectively assess greenwashing in non-financial sector, this paper scrutinizes public statements made by individual companies on social media platforms, such as Twitter. This approach is adopted as social media has become a prominent channel for companies to communicate their ESG initiatives and achievements to the public, making it a valuable source of data for evaluating their green credentials.

By employing Natural Language Processing (NLP) techniques, the study analyzes and quantifies the textual data contained within these public statements to determine the extent of a company's ESG marketing endeavors. This method allows for a systematic and unbiased evaluation of a company's ESG communication, helping to identify potential discrepancies between their marketing efforts and actual ESG performance.

The paper utilizes a pre-trained language representation model called BERT, which stands for Bidirectional Encoder Representations from Transformers, to analyze the language used in a company's environmental claims. Unlike other language representation models, BERT is designed to pre-train deep bidirectional representations from the unlabeled text by joint conditioning on both left and right context in all layers, making it highly effective in understanding complex language patterns. Among different BERT models, the paper chooses FinBERT[12] to classify ESG sentences in the textual data. FinBERT has been trained on a massive amount of financial news articles and documents to capture the financial domain-specific language, enabling it to accurately identify and classify ESG-related statements made by companies. FinBERT has outperformed other state-of-the-art models on various sentiment analysis benchmarks, as stated in "FinBERT: Financial Sentiment Analysis with Pre-trained Language Models" (Yang et al., 2020). The paper further fine-tuned FinBERT-ESG on 100 manually annotated sentences from companies' tweets[13]. This additional fine-tuning allows the model to better understand the language and context used in social media posts, which can provide insights into a company's ESG marketing efforts.

We then use the RepRisk RRI (Reputation Risk Index) to assess the company's true environmental risk. Developed by RepRisk, a global company specializing in ESG data, the RRI is a quantitative measure of a company's ESG risk exposure. The score ranges from 0 to 100 and reflects the severity and frequency of a company's ESG-related issues and incidents, with higher scores indicating higher risk exposure. The use of RRI allows for an objective evaluation of a company's environmental risk, which serves as a useful benchmark for comparison with its marketing claims.

[12] For more details, see `https://github.com/yya518/FinBERT`

[13] See Appendix B for examples of basic inputs and outputs of the FinBERT-ESG model.

The study utilizes a quarterly frequency for computation so that we could add companies' quarterly fundamental data in further analysis. In order to derive the Greenwashing Risk Score, we initially calculate the overall ESG marketing score for each company, which involves averaging the ESG score generated by FinBERT-ESG based on all the textual data present in the company's tweets, including replies and comments, during that quarter. The ESG marketing score is on a scale of 0 to 1, with 0 indicating no ESG marketing efforts and 1 indicating maximum effort. Subsequently, the quarterly average RePRisk RRI (Reputational Risk Index) is used as the company's true ESG risk, with a higher RRI signifying greater ESG risk. Finally, the Greenwashing Risk Score is obtained by multiplying the ESG marketing score by the quarterly average RepRisk RRI, and dividing the product by 100, resulting in a score ranging from 0 to 1. A score of 0 indicates no greenwashing risk, whereas a score of 1 indicates maximum greenwashing risk.

4.2 Greenwashing Risk Score in the Financial Sector

Taking into account the unique characteristics of the finance industry, the research specifically targets individual ESG funds as the sample group, which is a more suitable unit of analysis for assessing greenwashing risk than individual financial institutions or asset managers. This approach allows for a more granular examination of greenwashing risk as it focuses on the specific ESG investments rather than broader entities that may have diverse investment portfolios.

To calculate the greenwashing risk score for each fund, the study employs the Morningstar Sustainable Rating for Funds[14], which evaluates the fund's actual ESG performance considering the quality of its investment portfolio. The Morningstar Sustainable Funds

[14] For details, see https://www.morningstar.com/articles/745796/introducing-the-morningstar-sustainability-rating-for-funds

rating is a five-globe rating system, with five globes indicating the highest level of sustainability standards. In this study, a score of 0 to 1 is assigned to each globe level in proportion to its scale. For ESG funds that are labeled as such[15], their ESG marketing score is simply set to 1, as they clearly market themselves as ESG funds with full effort. This assumption ensures that the analysis accurately captures the marketing efforts of funds that explicitly promote their ESG credentials.

The final greenwashing risk score for these ESG funds is then obtained by dividing 1 by the sustainable rating of the fund, and then standardizing it so that the final score is in the range of 0-1, with 0 meaning the lowest risk. This method allows for a standardized measure of greenwashing risk that takes into account both the marketing efforts and the actual ESG performance of the funds, enabling a more comprehensive assessment of the potential risk associated with each fund.

4.3 Identification Results

Based on the methodology described in the previous section, the greenwashing risk scores for each sample company and ESG fund were calculated and analyzed to identify trends and patterns.

First, for the non-financial sector, the companies were divided into two groups based on whether they were selected by ESG funds. The first group, referred to as the ”green” companies, comprises those that have been selected by the ESG funds. The second group, called the ”brown” companies, consists of those that have not been selected by the ESG funds. These two groups serve as the treatment and control groups, respectively, in our

[15] The paper uses the indicator of "sustainable investment" from Morningstar, which is yes if, in the prospectus or other regulatory lings of the fund, it is described as focusing on sustainability, impact investing, or environmental, social or governance factors. Funds must claim to have a sustainability objective, and/or use binding ESG criteria for their investment selection.

Table 4: Identification Results in the Non-financial Sector

	N	Mean	SD	Min	p25	p50	p75	Max
				Control Group (Brown)				
Greenwashing Risk	2440	0.108	0.141	0	0	0	0.196	0.613
RRI	2440	10.250	12.380	0	0	0	20.830	47.930
ESG Marketing Score	2440	0.331	0.111	0.141	0.247	0.317	0.401	0.630
				Treatment Group (Green)				
Greenwashing Risk	1640	0.113	0.125	0	0	0.087	0.164	0.613
RRI	1640	11.14	11.38	0	0	9.972	15.90	47.93
ESG Marketing Score	1640	0.323	0.105	0.141	0.240	0.316	0.391	0.630

difference-in-differences (DID) analysis. Table 4 shows the descriptive statistics for each group, providing an overview of the greenwashing risk scores, RRI, and ESG marketing scores for both green and brown companies.

As seen in Table 4, the mean greenwashing risk score for the green companies is slightly higher than that of the brown companies, although the difference is small. On the other hand, the mean reputational risk index (RRI) of the green companies is also higher, suggesting that green companies may face a greater risk to their reputation due to their involvement in ESG-related activities. The higher RRI for green companies may imply that these companies are more vulnerable to reputational damage if they are found to engage in greenwashing or fail to meet their ESG commitments. However, the brown companies have a higer mean ESG marketing score, indicating that these firms tend to spend more efforts on marketing their ESG-related activities.

Figure 1 shows the mean greenwashing of green companies over time and Figure 2 shows the mean greenwashing of brown companies. From 2019-Q3 to 2021-Q4, the mean greenwashing risk score for brown companies has generally increased. This trend could be attributed to a growing awareness of ESG-related issues and an increasing pressure on companies to demonstrate their sustainability efforts, which might inadvertently encourage greenwashing behavior.

Figure 1: Mean Greenwashing of Green Companies in the Nonfinancial Sector

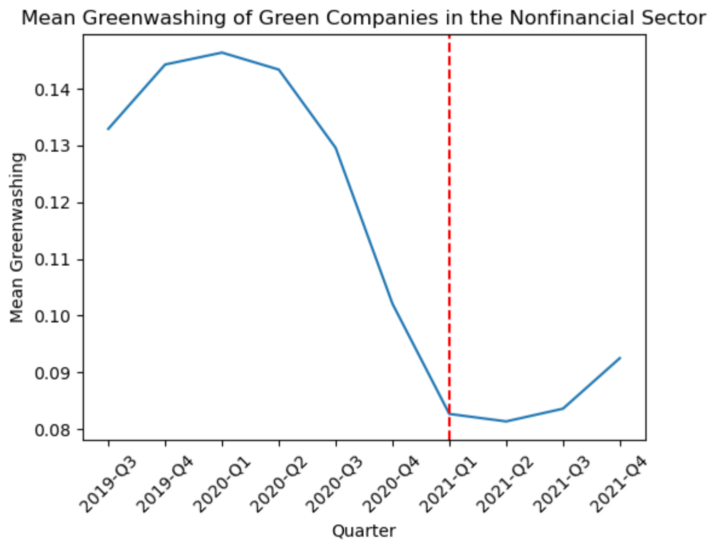
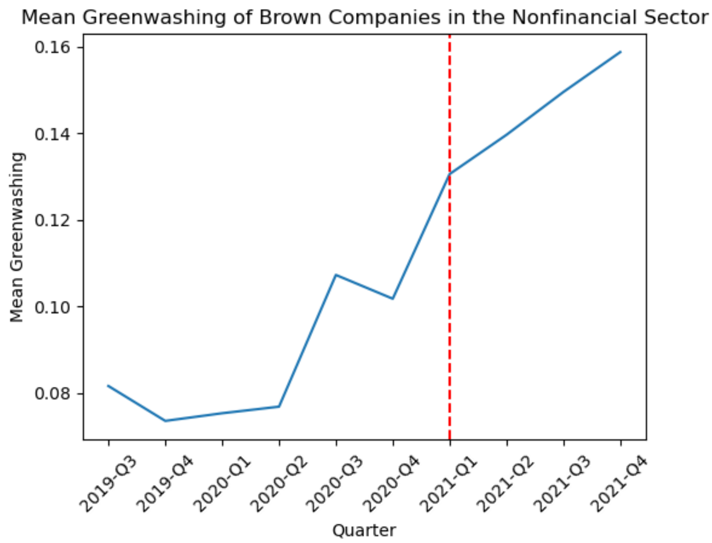
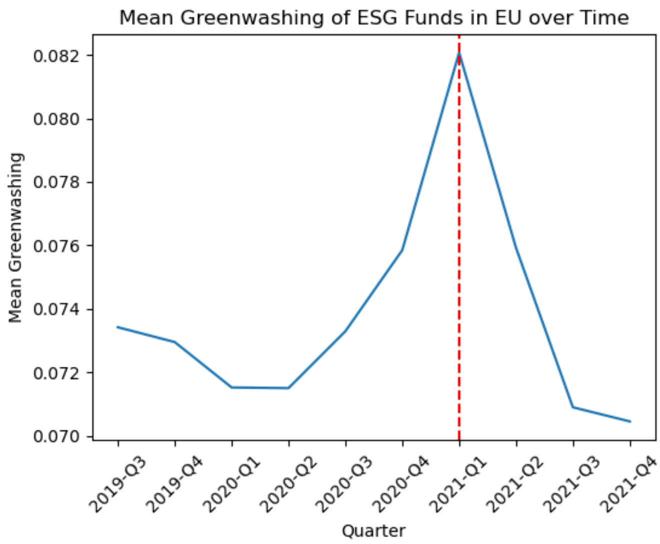


Figure 2: Mean Greenwashing of Brown Companies in the Nonfinancial Sector



However, it is worth noting that the mean greenwashing risk score of green companies declined before and after the implementation of the Sustainable Finance Disclosure Regulation (SFDR). This might imply that the SFDR has had a spillover effect in reducing greenwashing in the treatment group. The spillover effect might be the result of a pre-event trend, where companies in the treatment group started to improve their ESG practices and reduce greenwashing behaviors in anticipation of the regulation.

Figure 3: Mean Greenwashing of ESG Funds in EU over Time



Regarding the financial sector, the mean greenwashing risk score of the sample EU ESG funds for each quarter is plotted in Figure 3. The figure shows an upward trend in the mean greenwashing risk scores between 2019-Q3 and 2021-Q1. Following the SFDR implementation in 2021-Q1, the mean greenwashing risk score begins to decline. The noticeable decrease in greenwashing risk after the SFDR implementation underscores the potential effectiveness of such regulations in reducing greenwashing in the financial sector.

The mean greenwashing risk score for ESG funds in each EU country is shown in Figure 4 and the mean greenwashing risk score for ESG funds in each non-EU country or region is shown in Figure 5. These figures provide insights into the geographical distribution of greenwashing risk in ESG funds across different countries and regions.

Figure 4: Mean Greenwashing of ESG Funds in each EU Country over Time

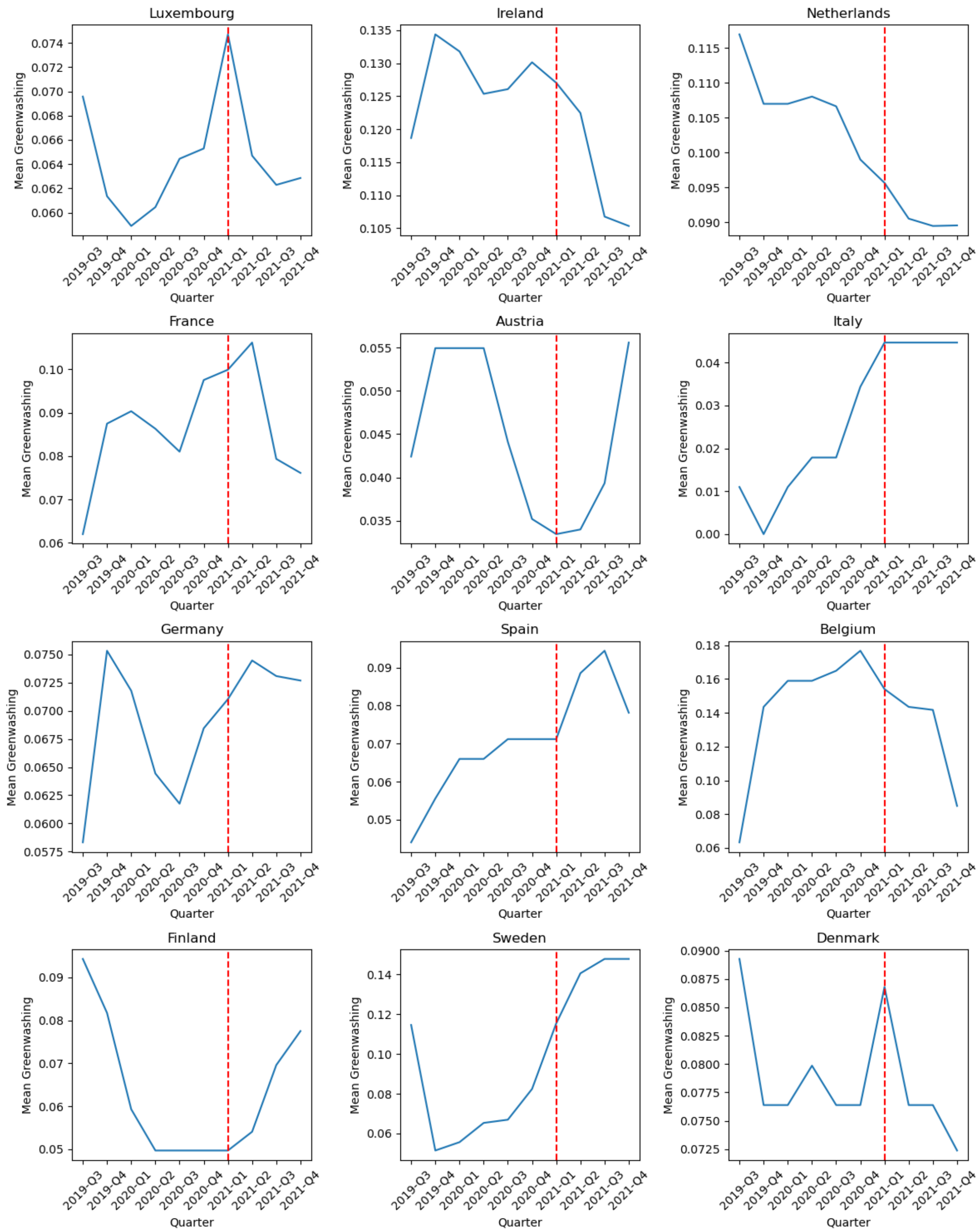
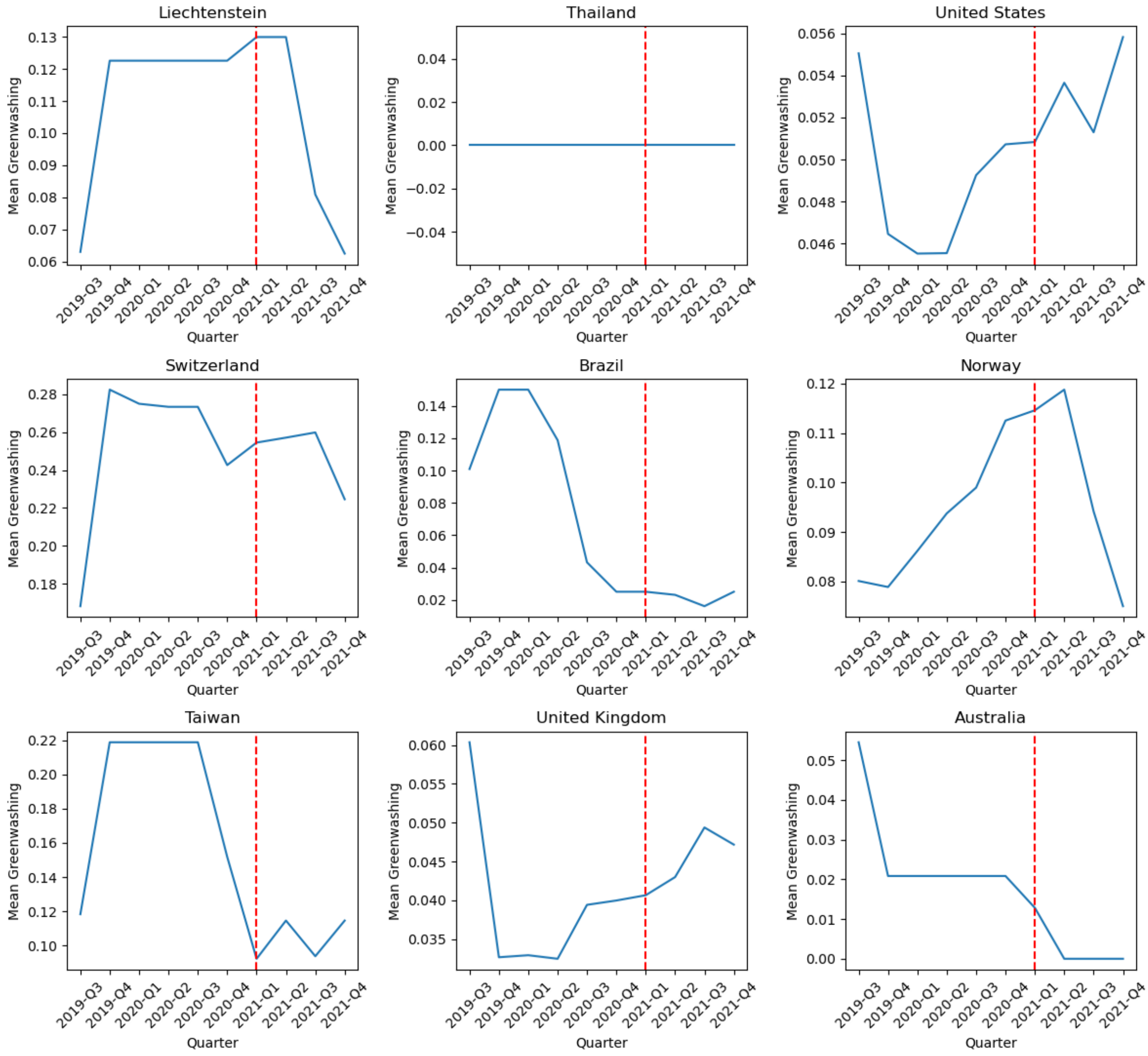


Figure 5: Mean Greenwashing of ESG Funds in non-EU Country or Region over Time



5 Effects of the SFDR on Greenwashing

5.1 Effects of SFDR on the Financial Sector

In this section, we investigate the impact of the Sustainable Finance Disclosure Regulation (SFDR) on reducing greenwashing risk in the financial sector. After winsorization to deal with abnormal values, we employ a difference-in-differences approach to estimate the causal effect of the SFDR on greenwashing. The baseline DID model can be specified as:

$$\mathit{Greenwashing}_{it} = \quad + \quad {}_1 \mathit{In\ EU}_i + \quad {}_2 \mathit{PostTreat}_t + \quad (\mathit{In\ EU}_i \quad \mathit{PostTreat}_t) + \mathbf{X}_{it} \quad + \quad {}_{it} \quad (1)$$

where $\mathit{Greenwashing}_{it}$ represents the greenwashing risk of fund i in period t, $\mathit{In\ EUi}$ is a binary variable indicating whether fund i's domicile is in the EU, which determines whether the fund subjects to SFDR, and $\mathit{PostTreat}_t$ is a binary variable that takes the value of 1 for the post-treatment period and 0 for the pre-treatment period. The coefficient of interest is , which captures the DID estimator of the SFDR's impact on greenwashing. $\mathbf{X}_{it}$ is a vector of control variables, including *log(Fund Size)*, *Fund Beta*, *Standard Deviation*, *Sharpe Ratio*, *return*, and *log(net asset per share)*, and $_{it}$ is error term.

We estimate three different models, considering various sets of fixed effects to account for unobserved factors that may influence greenwashing:

Model 1: No fixed effects are included in this baseline model.

Model 2: This model includes both country and time fixed effects, which control for unobserved time-invariant characteristics of countries and common time trends.

Model 3: This model incorporates individual fund fixed effects and time fixed effects. We control for fund-specific factors that might influence greenwashing, such as fund management styles, investment strategies, or governance structures.

Table 5: DID Estimation of the Effects of SFDR on Greenwashing in the Financial Sector

	(1) Greenwashing	(2) Greenwashing	(3) Greenwashing
In EU PostTreat	-0.007**	-0.008**	-0.007**
	(0.003)	(0.003)	(0.003)
Control Variables:			
(1) Fund Specific Time-invariant	Yes	Yes	No
(2) Fund Specific Time-variant	Yes	Yes	Yes
Country FE	No	Yes	No
Time FE	No	Yes	Yes
Fund FE	No	No	Yes
N	18650	18650	18650
R-squared	0.016	0.130	0.005

Standard errors in parentheses

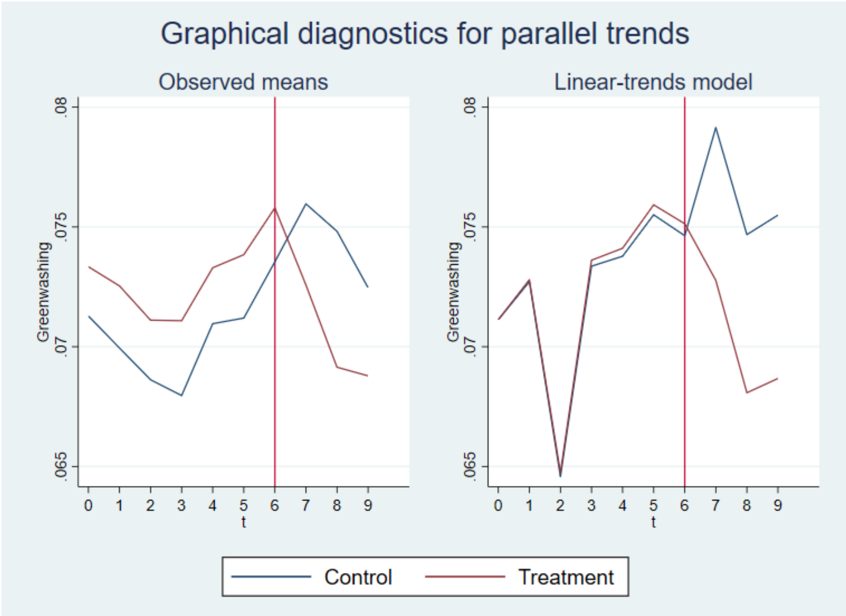
* p < 0:1, ** p < 0:05, *** p < 0:01

The results are presented in Table 5. By estimating the models with different fixed effects, we aim to ensure that the estimated causal effect of SFDR on greenwashing is robust to the inclusion of various unobserved factors.

Following the results presented above, we find a negative and statistically significant relationship between the interaction term (In EU PostTreat) and greenwashing across all three models. Specifically, the estimated coefficients for the interaction term are -0.007 ($p < 0.05$) for Model 1, -0.008 ($p < 0.05$) for Model 2, and -0.007 ($p < 0.05$) for Model 3. This consistently suggests that the SFDR is effective in reducing greenwashing risk among ESG funds affected by the regulation.

To further assess the validity of our model, it is crucial to examine the common trend assumption, which is a prerequisite for the DID analysis. Figure 6 provides graphical diagnostics for the parallel trends. As the figure demonstrates, there is indeed a common trend between the treatment and control groups. Also, we employ an event study framework to test the impact of the SFDR on greenwashing before and after its implementation.

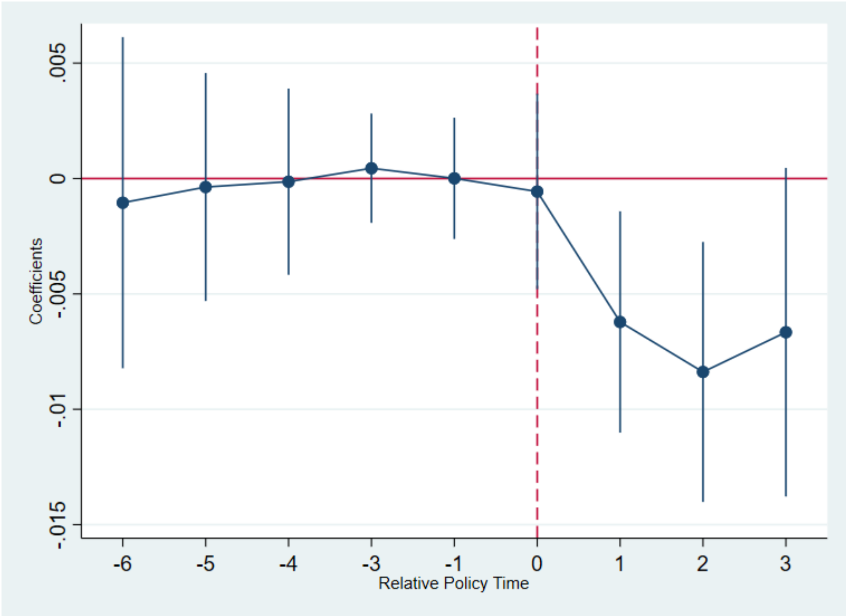
Figure 6: Common Trend of the Greenwashing Risk of ESG Funds



By creating pre-treatment and post-treatment period dummies and interacting them with the treatment group indicator (In EU), we can observe the evolution of greenwashing among ESG funds affected by the regulation over time. The event study graph generated from these specifications (Figure 7, the second period before SFDR implementation is dropped to avoid multicollinearity) displays the estimated coefficients for the interaction terms over time, with a vertical dashed line indicating the policy implementation. As shown is the figure, before the treatment period, the estimated coefficients for the interaction terms are not significantly different from zero, implying that the treatment and control groups follow parallel trends in greenwashing.

Considering the potential endogeneity issues, such as unobserved factors that may affect both the treatment status and the outcome of interest (greenwashing), we also employ a Propensity Score Matching-Difference-in-Differences (PSM-DID) approach. This method combines the advantages of both propensity score matching and difference-in-differences analysis, thereby addressing potential biases arising from endogeneity and unobservable time-invariant confounders.

Figure 7: Event Study



To implement the PSM-DID approach, we first estimate the propensity scores using a logit model with the treatment indicator as the dependent variable and the relevant control variables. Then, we perform matching based on the estimated propensity scores, using a caliper of 0.05 and one nearest neighbor. Finally, we estimate the treatment effect on the treated by comparing the average treatment effect (ATE) in the matched sample, using a DID regression model that includes both time and fund-fixed effects(Model 3). The results of the PSM-DID analysis are presented in Table 6.

The estimated coefficient for the cross product (In EU PostTreat) is -0.011 ($p < 0.01$), indicating a negative and statistically significant relationship between the SFDR and greenwashing. This result is consistent with the findings from our previous DID analysis, further strengthening the evidence that the SFDR has effectively reduced greenwashing risk among ESG funds within the European Union.

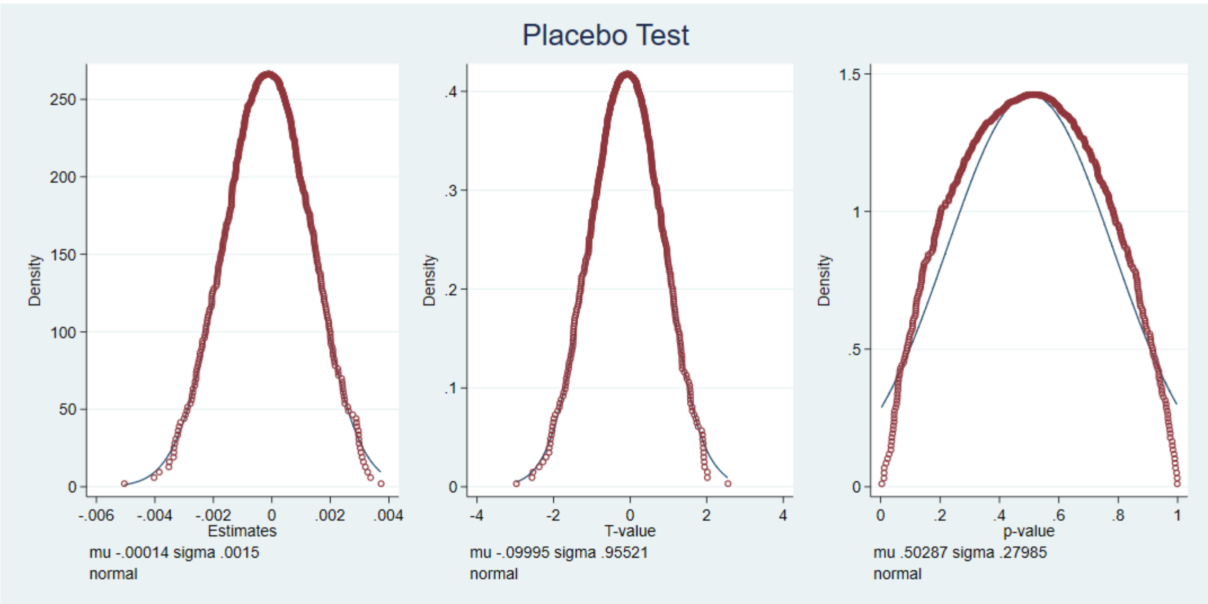
To assess the robustness of our findings, we also conduct a placebo test by permuting the treatment variable and estimating the fixed effects regression model with the same covariates. This process is repeated for 500 iterations, generating a distribution of placebo

Table 6: PSM-DID Results

	Greenwashing
In EU PostTreat	-0.011***
	(0.003)
ln(Net Assets per Share)	0.002
	(0.001)
Return	-0.000
	(0.000)
Constant	0.046**
	(0.022)
N	5986
R-squared	0.008

Standard errors in parentheses
* p < 0:1, ** p < 0:05, *** p < 0:01

Figure 8: Placebo Test



treatment effect estimates. The distributions of the estimated coefficients, t-values, and p-values for the placebo tests are presented in Figure 8. The actual treatment effect stands out from the placebo estimates, suggesting that our main results are unlikely to be driven by confounding factors or spurious relationships.

To sum up, the empirical results from our difference-in-differences analysis provide evidence that the implementation of the SFDR has contributed to a reduction in greenwashing practices among ESG funds affected by the regulation.

5.2 Spillover Effects of SFDR on the Non-Financial Sector

In this section, we investigate the spillover effect of the SFDR on reducing greenwashing in the non-financial sector using an event study framework. As mentioned in the previous sections, unlike the SFDR in the financial sector, we cannot precisely determine the timing of the possible spillover. This uncertainty calls for an event study approach, which is particularly useful in our context because it enables us to explore the potential dynamic effects of the SFDR on greenwashing in the non-financial sector. This approach is based on the assumption that, in the absence of the SFDR, the pre-treatment trends in greenwashing would have continued unchanged for the treated and untreated groups (Common Trend), which we need to test and validate to ensure the credibility of our findings.

We estimate a dynamic version of the DID model, allowing for different treatment effects at each period relative to the event (SFDR). The model is given by:

$$Greenwashing_{it} = \quad + \sum_{k=\;\;K}^{K} \quad {}_k \,(Treated_i \quad EventTime_{k;t}) + \mathbf{X}_{it} \quad + \quad {}_i + \quad {}_t + \quad {}_{it} \qquad (2)$$

where $EventTime_{k;t}$ is a series of binary variables indicating the time relative to the event, and ${}_k$ captures the treatment effects at each period k. $\mathbf{X}_{it}$ includes control variables such as ln(total debt), ln(cash flow), ln(total asset), pretax roa, ln(ebitda), ln(cash and short-term investment), and ln(market cap).

As shown in Figure 1, we can see a downward trend since 2020-Q1. To examine the time period from 2020-Q2[16] to 2021-Q1 (SFDR), we exclude the period immediately before 2020-Q2 as the reference period. Consequently, the estimated treatment effects are relative to this period.

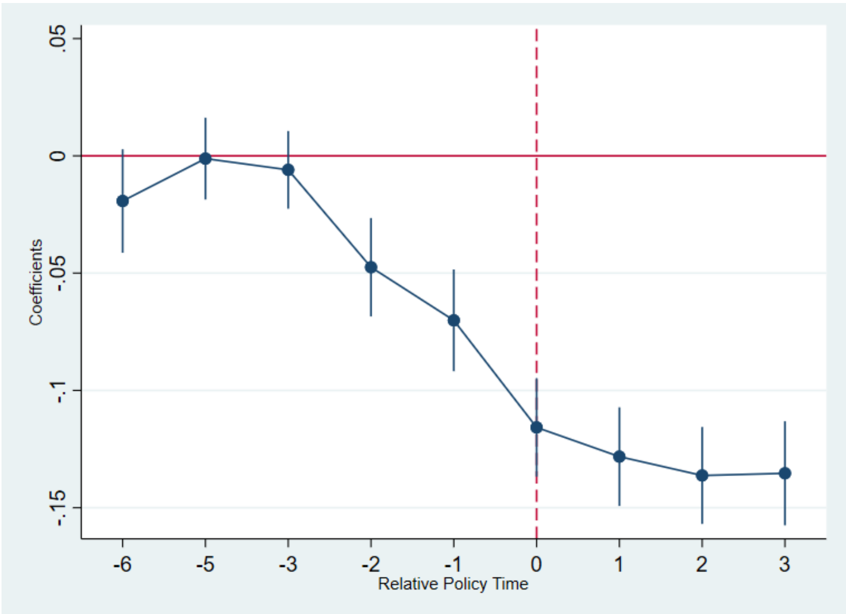
[16] The first details of the SFDR requirements were published by the European Supervisory Authorities [ESAs] in April 2020 in a consultation paper.

Table 7: Event Study Results

	greenwashing	
pre_6	-0.019*	(0.011)
pre_5	-0.001	(0.009)
pre_3	-0.006	(0.008)
pre_2	-0.047***	(0.011)
pre_1	-0.070***	(0.011)
current	-0.116***	(0.011)
pos_1	-0.128***	(0.011)
pos_2	-0.136***	(0.011)
pos_3	-0.135***	(0.011)
Observations	4080	
R^2	0.140	

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 9: Event Study Results



The results presented in Table 7 and Figure 9 illustrate the effect of SFDR on greenwashing across various time periods relative to the event. Our analysis relies on the critical assumption that the observed changes in greenwashing are directly attributable to the introduction of SFDR. To further substantiate this claim, Section 6 will delve into both theoretical conjectures and empirical tests, which will enhance the robustness of our findings and support the causal relationship between SFDR and greenwashing.

The negative and statistically significant coefficients for the pre-treatment periods (pre_2 to pre_1) suggest that greenwashing had already been decreasing prior to the introduction of SFDR. This could be due to the anticipation of upcoming SFDR(as the information of SFDR is out since pre_3), which prompted green companies to start adjusting their practices.

The "current" row captures the immediate effect of SFDR on greenwashing during the event period. The negative and statistically significant coefficient indicates a further reduction in greenwashing with the introduction of SFDR. This can be attributed to the mandatory disclosure requirements and the higher transparency standards imposed by SFDR for the financial sector, which discourage companies from engaging in greenwashing.

The coefficients for the post-treatment periods (pos_1 to pos_3) represent the changes in greenwashing relative to the reference period after the introduction of SFDR. The negative and statistically significant coefficients suggest that greenwashing has continued to decrease in the periods following the implementation of SFDR. This ongoing reduction can be explained by the increased compliance with SFDR regulations and the growing pressure from investors, consumers, and regulators to align corporate actions with sustainable development goals.

To do robustness check, we have chosen different reference periods to conduct the event study, with the results displayed in Table 8 and Figure 10. The results across all four models consistently show a negative and significant relationship between the greenwashing variable and the SFDR. In general, the greenwashing variable's coefficient becomes more negative and statistically significant as we move from the pre-event period to the post-event period. The consistency of these results indicates that the relationship between greenwashing and the event is not driven by the choice of reference period.

Table 8: Results of the Event Study with Different Reference Periods

	Greenwashing			
	(1)	(2)	(3)	(4)
pre_6	-0.019*	-0.013	0.028**	0.051***
	(0.011)	(0.010)	(0.012)	(0.012)
pre_5	-0.001	0.005	0.046***	0.069***
	(0.009)	(0.009)	(0.011)	(0.011)
pre_4		0.006	0.047***	0.070***
		(0.008)	(0.011)	(0.011)
pre_3	-0.006		0.042***	0.064***
	(0.008)		(0.010)	(0.010)
pre_2	-0.047***	-0.042***		0.023**
	(0.011)	(0.010)		(0.009)
pre_1	-0.070***	-0.064***	-0.023**	
	(0.011)	(0.010)	(0.009)	
current	-0.116***	-0.110***	-0.068***	-0.046***
	(0.011)	(0.010)	(0.010)	(0.008)
pos_1	-0.128***	-0.122***	-0.081***	-0.058***
	(0.011)	(0.010)	(0.011)	(0.010)
pos_2	-0.136***	-0.130***	-0.089***	-0.066***
	(0.011)	(0.009)	(0.011)	(0.011)

Standard errors in parentheses
$p < 0{:}1$, $p < 0{:}05$, $p < 0{:}01$

Table 9: DID Estimation of the Effects of SFDR on Greenwashing in the Non-Financial Sector

	(1) Greenwashing	(2) Greenwashing	(3) Greenwashing	(4) Greenwashing
DID	-0.105***	-0.105***	-0.105***	-0.105***
	(0.006)	(0.006)	(0.006)	(0.006)
Control Variables:	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Country FE	No	No	Yes	Yes
N	4080	4080	4080	4080
R-squared	0.122	0.122	0.122	0.122

Standard errors in parentheses
* $p < 0{:}1$, ** $p < 0{:}05$, *** $p < 0{:}01$

Figure 10: Event Study Results

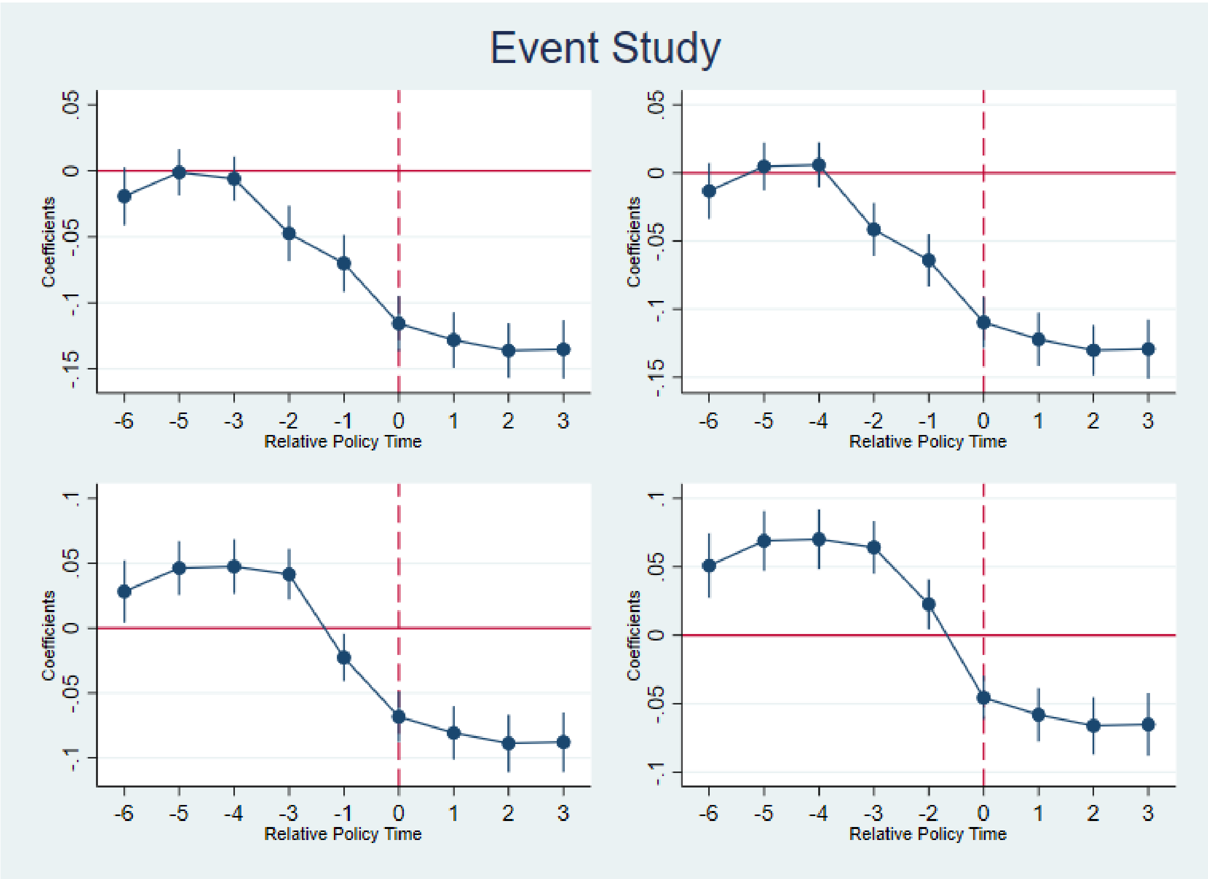
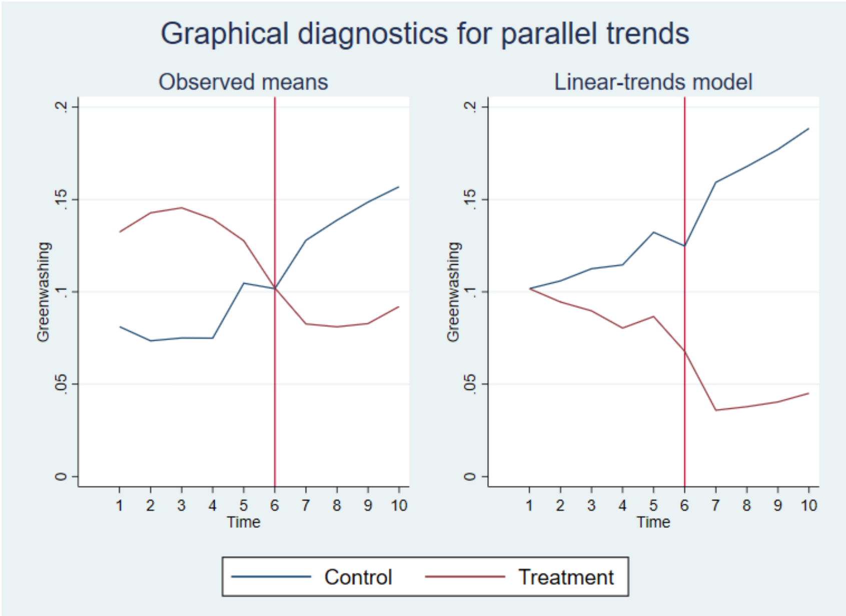


Figure 11: Graphcial Disgnostics of Common Trend



In addition to the event study, a standard Difference-in-Differences (DID) analysis was also conducted to further validate the results, which are presented in Table 9. The DID analysis strengthens the evidence for the impact of SFDR on greenwashing. By comparing the treatment and control groups before and after the introduction of SFDR, the DID analysis helps to control for unobserved factors that may have affected greenwashing over time. The graphical diagnostic test (Figure 11) supports the common trend assumption, indicating that the treatment and control groups followed a similar trend before the event. This is a crucial assumption for the validity of the DID estimation. The placebo test (Figure 12) demonstrates that the observed changes in greenwashing are not driven by spurious factors or pre-existing trends but are attributable to the introduction of SFDR.

In summary, our analysis suggests that the introduction of SFDR has had a significant and persistent impact on reducing greenwashing in the non-financial sector.

Figure 12: Placebo Test

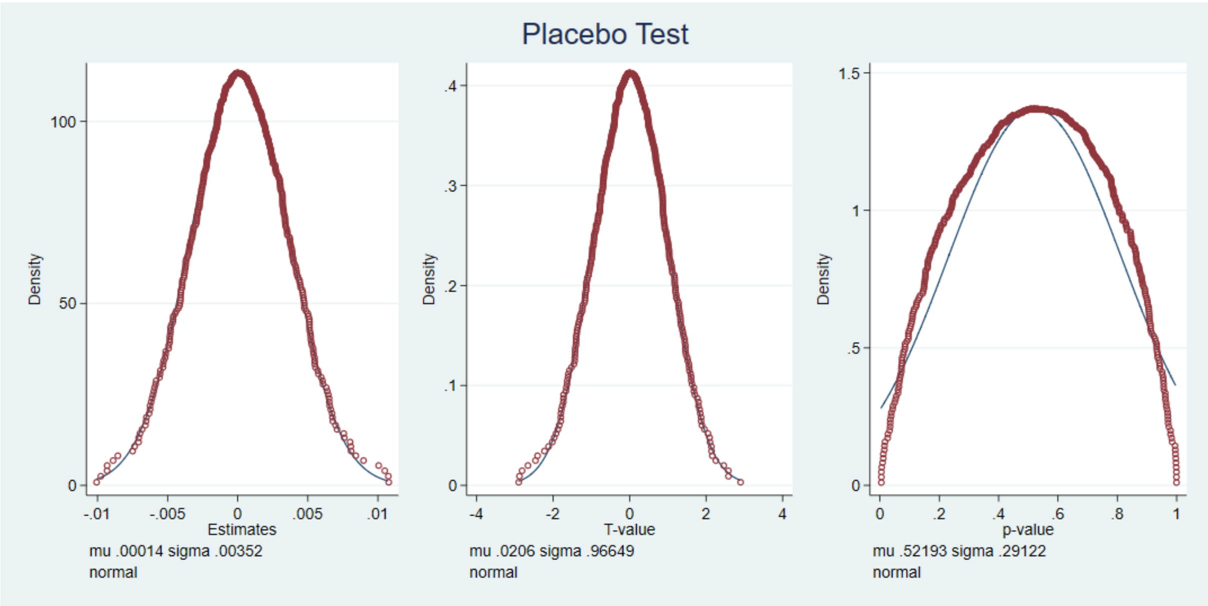
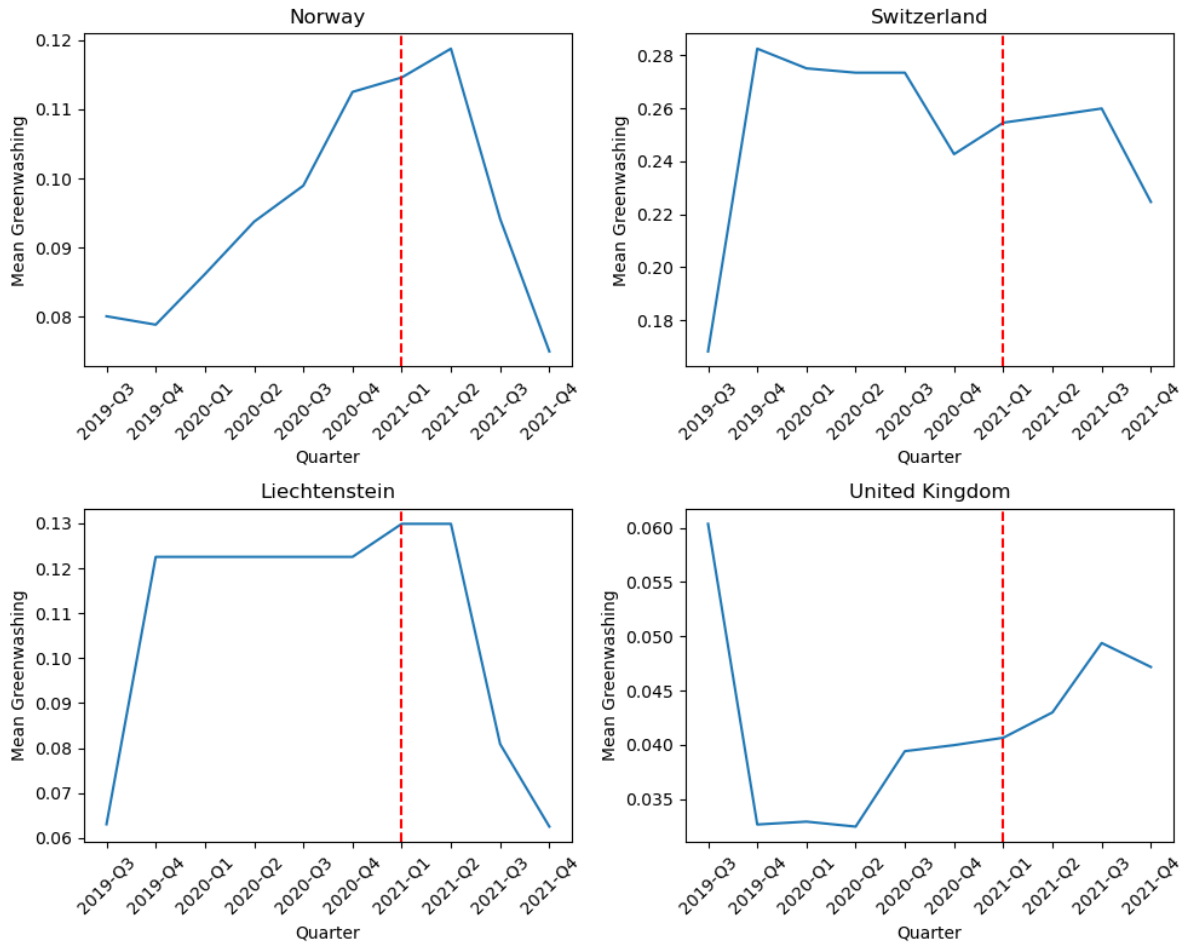


Figure 13: Mean Greenwashing of ESG Funds in each non-EU Neiboring Country



5.3 Spillover outside EU

In this section, we further investigate whether the SFDR has an impact on funds in countries outside the EU. If so, this would affect the Stable Unit Treatment Value Assumption (SUTVA) underlying our DID analysis. SUTVA is an essential assumption because it ensures that the treatment effect of the regulation is not spillover to untreated units, thus enabling a clean causal interpretation of the treatment effect. Violation of the SUTVA assumption may lead to biased estimates of the treatment effect.

First, we start by examining the average greenwashing risk of funds over time for some countries in Europe but not in the EU (Figure 13). We find that for Norway, Switzerland, and Liechtenstein, the mean greenwashing risks for funds seem to have decreased after the implementation of the SFDR. This could be because these countries have stronger economic ties with the EU and are more likely to be influenced by the regulations. However, we do not observe a similar pattern in the United Kingdom. Therefore, we set up two new models to test the SUTVA assumption in our model and sample. We select Norway, Switzerland, and Liechtenstein as neighboring countries and generate an indicator variable, Neigh, which takes the value of 1 if the fund is domiciled in one of these countries and 0 otherwise. We estimate the potential spillover effect of the SFDR on the neighboring countries by including the interaction term between Neigh and Post. The two new models are specified as follows:

$$Greenwashing_{it} = \quad + \quad (InEU_i \quad Post_t) + \quad (Neigh_i \quad Post_t) + \mathbf{X}_{it} \quad + \quad _i + \quad _t + \quad _{it}$$

Where captures the DID estimator of the SFDR's impact on greenwashing and captures the potential spillover effect of the SFDR on the neighboring countries.

Table 10: SUTVA Analysis: SFDR Spillover Effects on Non-EU Countries

	(1) Greenwashing	(2) Greenwashing
Treatment Effect	-0.008**	-0.007**
	(0.003)	(0.003)
Neighbour Effect	-0.000	-0.001
	(0.009)	(0.006)
Control Variables:		
(1) Fund Specific Time-invariant	Yes	No
(2) Fund Specific Time-variant	Yes	Yes
Time FE	Yes	Yes
Individual FE	No	Yes
Country FE	Yes	No
N	18650	18650
R-squared	0.130	0.005

Standard errors in parentheses

* $p < 0{:}1$, ** $p < 0{:}05$, *** $p < 0{:}01$

The models differ in their fixed effects and control variables: Model 1 includes country fixed effects and Model 2 includes fund fixed effects. Both include time fixed effects.

The results in Table 10 show that the coefficient for the treated variable is negative and statistically significant in both models, indicating a reduction in greenwashing among treated funds. However, the coefficient for the spillover is not statistically significant in either model, suggesting that there is no evidence of a spillover to the neighboring countries: Norway, Switzerland, and Liechtenstein. This finding supports the validity of the SUTVA assumption in our DID analysis within the financial sector, strengthening the credibility of our results.

However, assessing the spillover effects outside the EU in the non-financial sector poses several challenges, including dealing with sectoral heterogeneity, home bias of funds, regulatory diversity and data limitation. A more reasonable identification strategy is also needed. Therefore, the spillover effects outside EU in the non-financial sector have not been investigated in the current study.

6 Investigating the Spillover Channels

6.1 Empirical Facts

Table 11: DID Estimation of the Effects of SFDR on RRI(Reputational Risk Index)

	(1)	(2)	(3)	(4)
	RRI	RRI	RRI	RRI
DID	-9.986	-9.986	-9.986	-9.986
	(0.480)	(0.480)	(0.480)	(0.480)
Control Variables:	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Country FE	No	No	Yes	Yes
N	4080	4080	4080	4080
R-squared	0.208	0.208	0.208	0.208

Standard errors in parentheses
$p < 0{:}1$, $p < 0{:}05$, $p < 0{:}01$

Table 12: DID Estimation of the Effects of SFDR on ESG Marketing

	(1)	(2)	(3)	(4)
	ESG Mkting	ESG Mkting	ESG Mkting	ESG Mkting
DID	0.004	0.004	0.004	0.004
	(0.007)	(0.007)	(0.007)	(0.007)
Control Variables:	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Country FE	No	No	Yes	Yes
N	4080	4080	4080	4080
R-squared	0.001	0.001	0.001	0.001

Standard errors in parentheses
$p < 0{:}1$, $p < 0{:}05$, $p < 0{:}01$

To explore the channels through which SFDR affects greenwashing in non-financial sectors, we naturally break down the Greenwashing score in the non-financial sector into two components: ESG marketing efforts and actual ESG performance(RRI) of companies. Then we use these two components as new dependent variables for DID analysis as before.

Table 11 presents the DID estimation results of the effects of SFDR on RRI. As seen in the table, the DID coefficient is consistently negative and highly significant across all four specifications, suggesting that SFDR has a significant negative impact on the RRI of non-financial firms. This finding implies that the implementation of SFDR has reduced the reputational risk exposure(aka increase real ESG performance) for non-financial pubic treatment group firms.

Table 12 displays the DID estimation results for the effects of SFDR on ESG marketing efforts. The DID coefficient in this case is positive but not statistically significant across all four specifications. This finding indicates that SFDR has no significant impact on the ESG marketing efforts of non-financial firms, suggesting that the regulation might not have incentivized non-financial companies to substantially increase their ESG marketing.

These findings suggest that the SFDR impacts the non-financial sector by increasing the incentives for non-financial firms to enhance their ESG performance while maintaining their original levels of ESG marketing. Instead of engaging in deceptive reporting or excessive marketing, non-financial companies appear to adopt a "do more than say" approach, which leads to a reduction in greenwashing risk. Consequently, the actual ESG performance of non-financial firms improves, aligning more closely with their marketing claims and mitigating their exposure to reputational risks. In the following sections, we provide theoretical explanations for this channel.

6.2 An Equilibrium Model in Sustainable Investment

Why do companies want to increase their ESG performance following the implementation of SFDR? To explain this channel, we consider a theoretical model based on an extension of the sustainable investment equilibrium model by Pástor et al. (2021).

Our model aims to demonstrate that as the SFDR reduces greenwashing in the financial sector, the green premium associated with real ESG performance increases, and consumers, in general, have lower expected returns for green assets. Consequently, improving genuine ESG performance becomes more profitable, as it can reduce a company's cost of capital. Therefore, non-financial sector firms are incentivized to enhance their true ESG performance. The key assumptions are:

Assumption 1: A significant group of investors invests in non-financial firms through financial sector entities such as funds, asset managers, and other intermediaries.

Assumption 2: Unlike individual consumers, the financial sector evaluates non-financial companies using a relatively objective approach. Instead of focusing on the marketing efforts of firms, they concentrate on the real ESG performance of the companies.

In this adaptation of the sustainable investment equilibrium model by Pástor et al. (2021), we introduce a financial sector greenwashing risk parameter, , to account for the impact of financial sectors' greenwashing risk on investor preferences. The model consists of a single period with N firms, each having an observable ESG characteristic g_n.

Agents derive utility from both wealth and the ESG characteristics of their stock holdings. Each agent i has exponential utility with a benefit vector that combines agent-specific and firm-specific components:

$$b_i = d_i(1 \quad)g \tag{3}$$

Here, d_i 0 represents agent i's "ESG taste," while captures the greenwashing risk(higher fees charged by the financial sector for greener funds). The benefit vector shows that agent i derives a nonpecuniary benefit of $d_i(1 \quad)g_n$ from holding stock n. Higher values of d_i correspond to stronger preferences for the ESG characteristics of holdings.

Agent i maximizes their utility by choosing the optimal portfolio X_i:

$$\max X_i \mathrm{E} \left[e^{\ A_i \tilde{W}_{1i} \quad b_i' X_i} \right] \tag{4}$$

subject to the budget constraint, where $\tilde{W}_{1i}$ is agent i's wealth at time 1 and A_i is absolute risk aversion. The first-order condition for the optimal portfolio choice X_i yields:

$$X_i = \frac{1}{a}\Sigma^{\ 1} \qquad + \frac{1}{a} b_i \tag{5}$$

where $a \quad A_i W_{0i}$ is agent i's relative risk aversion, and Σ is the covariance matrix of stock returns.

Assuming all agents have the same relative risk aversion, a, market clearing conditions require that the market portfolio of stocks, w_m, satisfies:

$$w_m = \frac{1}{a}\Sigma^{\ 1} \quad + \frac{\bar{d}}{a^2}\Sigma^{\ 1}(1 \qquad)g \tag{6}$$

where $\bar{d}$ is the wealth-weighted mean of d_i.

We assume that the market portfolio is ESG-neutral, i.e., $w_m' g = 0$. Combining this with the market clearing conditions, we obtain the relationship between the market equity premium, ${}_m$, and the variance of the market return, ${}^2_m$: $a = \frac{{}_m}{{}^2_m}$.

Our main finding reveals that in equilibrium, the expected excess returns are:

$$= \ {}_m \ {}_m \qquad \frac{\bar{d}}{a}(1 \qquad)g \tag{7}$$

This equation highlights that expected excess returns deviate from their CAPM values, ${}_m \ {}_m$, as a result of investors' ESG preferences and the influence of the greenwashing risk parameter, . Provided that a and $\bar{d}$ remain positive, and expected returns are inversely related to the real ESG performance of companies.

Investors with ESG preferences tend to pay higher prices for greener firms, which in turn leads to lower expected returns for these firms. The introduction of the greenwashing risk parameter, , reflects the impact of financial sectors' greenwashing risk on investor preferences, further modifying the expected returns on stocks.

Specifically, the influence of on expected returns can be understood as follows: when increases, the greenwashing effect becomes more pronounced, and the financial sector tends to charge higher fees for the same level of greenness(this is in line with the incentive of greenwashing of funds), causing investors to perceive a reduced nonpecuniary benefit from holding greener stocks. This results in a smaller deviation from the CAPM values.

According to the model, a reduction in the greenwashing risk parameter, , due to the effectiveness of regulations like SFDR, leads to an increase in the perceived nonpecuniary benefit for investors holding greener stocks. Consequently, investors are willing to pay higher prices for such stocks. As a result, the expected returns for greener companies decrease, which reduces their cost of capital.

The model does not explicitly discuss the impact of a reduced cost of capital on firms' true ESG performance. However, it is reasonable to infer that, with a lower cost of capital, greener firms may find it more economically attractive to invest in projects and initiatives that enhance their environmental, social, and governance performance.

In conclusion, the model demonstrates that if regulations like SFDR are effective in reducing greenwashing risk, they will affect the expected returns of greener firms. This, in turn, may influence the firms' decisions to invest in improving their true ESG performance, although the model does not provide direct evidence of this relationship.

6.3 Choosing the Optimal ESG Marketing Effort

The previous model primarily explains the channel of SFDR in increasing non-financial companies' real environmental performance. However, the empirical results indicate that SFDR does not have a significant effect on non-financial companies' ESG marketing efforts. In this section, we provide a simple model that might explain this observation.

Consider a set of companies $N = 1, 2, \ldots, n$ competing in a market. Each company $i \in N$ aims to choose the optimal ESG marketing effort, denoted by the fraction $_i$ of its marketing statements dedicated to ESG information. The choice of ESG marketing effort by company i affects the choices made by other companies in the market. The profit function of company i is given by $_i(_i, \; _i)$, where $_i$ represents the ESG marketing efforts of all other companies except i. We assume that the profit function is strictly concave in $_i$.

The objective of each company is to maximize its profit by choosing the optimal level of ESG marketing effort, considering the choices made by its competitors:

$$\begin{aligned} &\text{maximize} \quad _i(_i, \; _i) \\ &\text{subject to} \quad 0 \quad _i \quad 1 \end{aligned}$$

This problem can be modeled as a simultaneous-move non-cooperative game, in which each company chooses its ESG marketing effort to maximize its profit, given the ESG marketing efforts chosen by its competitors. In equilibrium, we seek a set of ESG marketing efforts $= (_1, \; _2, \ldots, \; _n)$ such that no company has an incentive to deviate.

A Nash equilibrium in this game is a strategy profile satisfying the following condition for all companies $i \in N$:

$$\frac{@ \quad i \quad i; \quad i}{@ \quad i} = 0; \quad 8i \; 2 \; N$$

This model suggests that companies choose their ESG marketing effort considering the trade-off between the benefits of increased ESG marketing, the diminishing returns from this effort and the strategic interactions with their competitors. If SFDR does not significantly affect this trade-off or the strategic interactions, we would expect to observe no substantial change in the ESG marketing efforts of non-financial companies. In this context, let us provide a more detailed explanation of why SFDR might not affect the optimal ESG marketing effort, , for non-financial companies.

First, we assume that the SFDR primarily affects the financial sector by enhancing transparency and disclosure requirements. This could lead financial companies to focus more on the real ESG performance of non-financial companies (ESG index) instead of their marketing efforts. Consequently, if the SFDR does not significantly alter the competitive landscape of the non-financial sector, the strategic interactions among non-financial companies would remain largely unchanged.

Second, let us consider the effect of SFDR on the trade-off between the benefits of increased ESG marketing and the diminishing returns from this effort. The introduction of SFDR may lead investors to pay more attention to the real ESG performance of non-financial companies rather than their marketing efforts. In this case, the marginal benefit of ESG marketing efforts for non-financial companies might decrease, as the focus shifts to real ESG performance. However, this effect might be offset by the fact that companies still need to maintain their visibility and reputation in the competitive market by engaging in ESG marketing, especially among customers who are not strictly following the financial sector's response to SFDR. Therefore, the net effect on the trade-off could be minimal.

Third, we assume that the SFDR does not significantly change the cost structure of ESG marketing efforts for non-financial companies. If the costs associated with ESG marketing remain relatively stable, the diminishing returns from ESG marketing efforts would not be significantly affected by the introduction of SFDR.

Taking these factors into account, we can conclude that the SFDR might not significantly affect the optimal ESG marketing effort, , for non-financial companies, as it does not substantially alter the strategic interactions among non-financial companies, nor the trade-off between the benefits of increased ESG marketing and the diminishing returns from this effort. The main impact of SFDR could be on the real ESG performance of non-financial companies, as the financial sector focuses more on companies' actual environmental, social, and governance performance rather than their marketing efforts.

6.4 Testing the Theorem

In this section, we use the eligibility for SFDR as an instrumental variable to test the theorem presented in the previous sections. This approach enables us to address potential endogeneity problems and establish a causal relationship between the greenwashing risk in the financial and non-financial sectors.

In the first stage, we apply the difference-in-differences (DID) model from Section 5.1 with individual fixed effects and time fixed effects:

$$\mathit{Greenwashing}_{it} = \quad + \quad (\mathit{In\ EU}_i \quad \mathit{PostTreat}_t) + \mathbf{X}_{it} \quad + \quad {}_i + \quad {}_t + \quad {}_{it} \tag{8}$$

Using this model, we obtain the fitted value of the greenwashing risk for the financial sector. In the second stage, we take the average of these fitted values across each fund, resulting in a time series of the fitted mean greenwashing risk for funds (denoted as $\overline{G\hat{S}_{F\,t}}$).

Table 13: Regression Results of the Second Stage

	(1) greenwashing	(2) greenwashing	(3) greenwashing	(4) greenwashing	(5) greenwashing
$\overline{GS}_{F\,t}$	1.490***	1.490***	1.490***	1.490***	1.490***
	(0.469)	(0.297)	(0.408)	(0.418)	(0.417)
ltotal_debt	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(.)	(0.000)	(.)
lcash_flow	0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(.)	(0.000)	(.)
ltotal_asset	0.001	-0.000	0.000	-0.001	0.000
	(0.001)	(0.001)	(.)	(0.001)	(.)
pretax_roa	-0.014*	-0.016*	0.000	-0.014*	0.000
	(0.008)	(0.009)	(.)	(0.008)	(.)
lebitda	0.000**	0.001**	0.000	0.000**	0.000
	(0.000)	(0.000)	(.)	(0.000)	(.)
lcash_shortin	0.000	0.001	0.000	0.001	0.000
	(0.001)	(0.001)	(.)	(0.001)	(.)
lmarket_cap	-0.002***	-0.002**	0.000	-0.002*	0.000
	(0.001)	(0.001)	(.)	(0.001)	(.)
_cons	0.106***	0.110***	0.093***	0.111***	0.093***
	(0.034)	(0.023)	(0.029)	(0.032)	(0.030)
Country FE	Yes	No	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	Yes
N	1490	1490	1490	1490	1490
r2	0.026	0.038	0.102	0.049	0.102

Standard errors in parentheses

* p < 0:05, ** p < 0:01, *** p < 0:001

In the second stage, we perform the following regression for treatment group companies in the non-financial sector:

$$Greenwashing_{it} = \quad + \quad \overline{GS}_{F\,t} + \mathbf{X}_{it} \quad + \quad_{i} + \quad_{it} \tag{9}$$

The regression results (Table 13) reveal a significant positive correlation between the mean greenwashing risk for funds ($\overline{GS}_{F\,t}$) and non-financial companies across all four models. This supports the earlier theorem, indicating that a decrease in funds' greenwashing risk is linked to a reduced risk for non-financial companies.

Table 14: Regression Results of the Second Stage

	(1) RRI	(2) RRI	(3) RRI	(4) RRI	(5) RRI
$\overline{GS_{Ft}}$	164.533***	164.533***	164.533***	164.533***	164.533***
	(41.616)	(25.986)	(36.421)	(37.322)	(37.230)
ltotal_debt	0.005	0.017	0.000	0.010	0.000
	(0.020)	(0.038)	(.)	(0.030)	(.)
lcash_flow	0.011	-0.009	0.000	0.014	0.000
	(0.011)	(0.017)	(.)	(0.019)	(.)
ltotal_asset	0.119	-0.021	0.000	-0.048	0.000
	(0.108)	(0.149)	(.)	(0.136)	(.)
pretax_roa	-0.996	-1.211	0.000	-1.205	0.000
	(0.898)	(1.100)	(.)	(0.862)	(.)
lebitda	0.028*	0.044*	0.000	0.040**	0.000
	(0.015)	(0.024)	(.)	(0.019)	(.)
lcash_shortin	-0.024	0.038	0.000	0.073	0.000
	(0.110)	(0.129)	(.)	(0.116)	(.)
lmarket_cap	-0.169**	-0.089	0.000	-0.111	0.000
	(0.063)	(0.088)	(.)	(0.084)	(.)
_cons	-7.884***	-7.907***	-8.668***	-7.740***	-8.668***
	(2.607)	(2.242)	(2.624)	(2.943)	(2.683)
Country FE	Yes	No	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	Yes
N	1490	1490	1490	1490	1490
r2	0.029	0.037	0.107	0.050	0.107

Standard errors in parentheses
* $p < 0{:}05$, ** $p < 0{:}01$, *** $p < 0{:}001$

I also test the theorem by modifying the dependent variable to RRI and ESG marketing effort to investigate their relationship with greenwashing risk in the financial sector. The results are shown in Table 14 and Table 15.

In accordance with the theorem positing that greenwashing in the financial sector influences RRI but not ESG marketing efforts in non-financial companies, the results from the second stage regressions lend support to the proposed theory. The significant positive impact of the fitted mean greenwashing risk for funds ($\overline{GS_{Ft}}$) on RRI across various specifications indicates that greenwashing in the financial sector indeed has a positive relation with the RRI of non-financial companies.

Table 15: Regression Results of the Second Stage

	(1) ESG MKT	(2) ESG MKT	(3) ESG MKT	(4) ESG MKT	(5) ESG MKT
$\overline{GS_{F\,t}}$	-0.387	-0.387	-0.387	-0.387	-0.387
	(1.741)	(1.309)	(1.616)	(1.656)	(1.652)
ltotal_debt	0.001	0.001	0.000	0.001	0.000
	(0.001)	(0.002)	(.)	(0.002)	(.)
lcash_flow	0.001	0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(.)	(0.001)	(.)
ltotal_asset	-0.001	-0.001	0.000	-0.003	0.000
	(0.003)	(0.006)	(.)	(0.006)	(.)
pretax_roa	-0.013	-0.006	0.000	0.005	0.000
	(0.025)	(0.025)	(.)	(0.038)	(.)
lebitda	-0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(.)	(0.001)	(.)
lcash_shortin	0.005	0.004	0.000	0.005	0.000
	(0.004)	(0.003)	(.)	(0.004)	(.)
lmarket_cap	-0.006	-0.008**	0.000	-0.006	0.000
	(0.004)	(0.003)	(.)	(0.004)	(.)
_cons	0.381**	0.417***	0.356***	0.410***	0.356***
	(0.156)	(0.089)	(0.116)	(0.129)	(0.119)
Country FE	Yes	No	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	Yes
N	1490	1490	1490	1490	1490
r2	0.013	0.031	0.100	0.039	0.100

Standard errors in parentheses
* $p < 0{:}05$, ** $p < 0{:}01$, *** $p < 0{:}001$

Conversely, the lack of a consistent significant relationship between the fitted mean greenwashing risk for funds ($\overline{GS_{F\,t}}$) and ESG marketing efforts indicates that greenwashing in the financial sector does not directly influence ESG marketing efforts in non-financial companies.

In summary, the regression results provide empirical evidence supporting the theorem that greenwashing in the financial sector affects greenwashing in the non-financial sector through reducing RRI but not ESG marketing efforts in non-financial companies.

7 Conclusion

This study has investigated the impact of the Sustainable Financial Disclosure Regulation (SFDR) on reducing greenwashing in both financial and non-financial sectors. To address the challenges of identifying and measuring greenwashing, we proposed an original method for the identification and analysis of greenwashing risk, aiming to provide a more objective and data-driven approach to studying ESG topics. This approach assesses the authenticity of an entity's environmental claims by comparing its marketing efforts to its actual environmental impact. To achieve this objective assessment, the paper employs a pre-trained NLP model called FinBERT to analyze the public statements of companies, ensuring a thorough and unbiased evaluation of their environmental claims.

Employing a Difference-in-Differences (DiD) approach, our findings indicate that the SFDR has effectively reduced greenwashing in the financial sector, as evidenced by the significant decrease in Greenwashing scores for EU-domiciled funds. Moreover, our event study reveals a dynamic and significant effect of the SFDR on reducing greenwashing in the non-financial sector. Spillover from the EU(where SFDR is employed) to other regions are also analyzed, the result shows that the impact of the SFDR on greenwashing is not statistically significant for neighboring countries of the EU.

By extending the sustainable investment equilibrium model and incorporating greenwashing risk, we provided a theoretical explanation for why the SFDR may incentivize companies in the non-financial sector to improve their ESG performance. Our model suggests that the SFDR reduces greenwashing risk in the financial sector, driving up the demand for genuine green investments and subsequently increasing the profits of the ESG factor, which encourages firms to enhance their actual environmental performance. This, in turn, leads to a reduction in greenwashing in the non-financial sector.

Furthermore, we developed a simple model to explain the lack of significant impact of the SFDR on the ESG marketing efforts of non-financial companies. We argue that the SFDR may not substantially affect the strategic interactions among non-financial companies or the trade-off between the benefits of increased ESG marketing and the diminishing returns from this effort.

Our empirical tests, supported by instrumental variable estimation, provided evidence consistent with our theoretical predictions. The results highlight the effectiveness of the SFDR in addressing greenwashing and promoting sustainable investments. However, it is important to note that our study focuses on the short-term effects of the SFDR. Future research should investigate the long-term effects of the regulation and explore whether the observed reductions in greenwashing persist over time.

In conclusion, this paper bridges the research gap by examining the effectiveness of the Sustainable Financial Disclosure Regulation (SFDR) in mitigating greenwashing across both financial and non-financial sectors. Additionally, the study explores the causal relationship between greenwashing in financial and non-financial sectors, providing a potential explanation for the discrepancies observed in prior literature. By addressing these research objectives, this study contributes to a more comprehensive understanding of greenwashing and its consequences, informing the development of effective policies and regulations that promote genuine ESG improvements and sustainable finance practices.

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9 Appendix

9.1 Appendix A

Description of Variables

Variable	Description
RepRisk Reputation Risk Index (RRI)	Index reflecting a company's environmental, social, and governance (ESG) risk exposure
Total Debt	The total amount of debt held by the company in the fiscal year in US dollars
Cash Flow	The net amount of cash and cash-equivalents being transferred into and out of a company during the fiscal year in US dollars
Total Assets, Reported	The total value of assets owned by the company, as reported for the fiscal year in US dollars
Pretax ROA	Ratio indicating the company's profitability before accounting for taxes, calculated by dividing the net income by total assets
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization in the fiscal year in US dollars
Cash and Short Term Investments	The total amount of cash and short-term investments held by the company in the fiscal year in US dollars
ISIN	International Securities Identification Number, a unique identifier for securities traded on public markets
Company Market Capitalization	The total market value of a company's outstanding shares in US dollars
Fund Size	The total value of assets managed by a fund
Beta 3 Year	A measure of a fund's sensitivity to market movements, calculated using 3 years of historical data
Standard Deviation	A measure of the dispersion of a fund's returns, indicating the level of volatility
Sharpe Ratio 3 Year	A risk-adjusted performance measure, calculated by dividing the excess return by the standard deviation of returns, using 3 years of historical data
Monthly Return	The percentage change in a fund's net asset value over a month
Morningstar Sustainable Rating for Funds	A rating system that assesses a fund's ESG performance relative to its peers, ranging from 1 (low) to 5 (high) stars
Net Asset per Share	The value of a fund's net assets divided by the number of its outstanding shares

9.2 Appendix B

The FinBERT Model

Sample Input

Sample Output

```
esg_results = esg_nlp([r"It's never been more important to be transparent about the progress \
                        we’re making toward a more sustainable and inclusive future",
                       "That's why McDonald's is releasing reporting that offers a detailed \
                        look at how we're making progress toward our ESG ambitions"])

esg_results
```

```
[{'label': 'Social', 'score': 0.9505437016487122},
 {'label': 'Social', 'score': 0.6995806694030762}]
```

For the tweets that were crawled, I first preprocessed the text by removing any URLs, mentions, and hashtags using regular expressions. Then, I separated the preprocessed text into training and testing sets. I input the preprocessed training text to fine-tune this pre-trained FInBERT model on my ESG classification task. The BERT model automatically performs tokenization, lowercasing, and removing stopwords during the fine-tuning process. The fine-tuned BERT model then encodes the preprocessed training text into dense vector representations that capture the semantic meaning of each tweet. Finally, I use the encoded text as input to my ESG classification model to predict the ESG marketing effors of each tweet in the preprocessed testing set.