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(GREEN)WASHING THE TRUST: CLIMATE INFORMATION AND BANKING POLICIES

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Abstract

Greenwashing, that is, the deceptive self-portrayal of companies as sustainable and environmentally friendly, is an increasingly relevant issue in finance. Identifying *greenwashers* is not a trivial task, given the difficulty of assessing firms' true environmental profiles, especially when relying on traditional data sources that generally overlook communication strategies and mass perceptions. Using granular credit data from the euro area banking system, we show that during the period 2019-2023, *greenwashers*, initially identified by combining information on firms' carbon emissions with an assessment of the reliability of their reporting, were able to borrow at lower interest rates than other companies. We then assess companies' environmental profiles by extracting textual information from newspapers and the internet. We find that sentiment scores based on firms' own websites are generally higher than those derived from newspapers, suggesting that companies use their communication channels to place greater emphasis on their sustainable image than is reflected in external sources. By integrating this textual metric with our initial proxy, we construct an alternative definition of *greenwashing*. Based on a sample of Italian firms, results obtained from this combined proxy are consistent with those derived from structured data alone. Finally, by introducing an unexpected contractionary monetary policy shock into our framework, we confirm the operation of the credit risk channel of monetary policy and find evidence of a reduction in the pricing benefits previously enjoyed by *greenwashers*.

JEL Classification: E52, C81, G21, Q50.

Keywords: greenwashing, banks, web-scraping, text analysis, sentiment scores.

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1 Introduction[1]

In recent years, climate change and the international initiatives aimed at preventing it have created pressure on companies, financial institutions, and governments to improve their environmental performance and reduce their carbon footprint. According to the United Nations Environment Programme (UNEP), one of the key vehicles to address climate change is the growing use of green financing, defined as the effort "*to increase the level of financial flows (from banking, micro-credit, insurance and investment) from the public, private and not-for-profit sectors to sustainable development priorities. A key part of this is to better manage environmental and social risks, take up opportunities that bring both a decent rate of return and environmental benefit, and deliver greater accountability.*"

Nevertheless, a major challenge in green financing is the presence of *greenwashing*, whereby companies provide misleading information or communication about their environmental and sustainability profiles. In particular, *greenwashing* arises when a firm's communication strategy to enhance its environmental reputation is not supported by reliable data and results, or is deliberately used to divert investors' attention from the company's true profile.

Greater transparency in corporate communication, whether driven by regulatory obligations or voluntary disclosure, can significantly affect firms' economic and reputational outcomes, as well as their relationships with the financial sector. Recently, COP27 (2022) released a how-to guide to ensure credible and accountable net-zero pledges, in which the United Nations declared zero tolerance for net-zero *greenwashing*.

In this respect, the EU Sustainable Finance Disclosure Regulation (SFDR) and the Non-Financial Reporting Directive (NFRD) aim to address measurement difficulties and anecdotal evidence of *greenwashing* in both financial and non-financial markets. Nonetheless, the lack of clear standards remains a bottleneck for their full application. For instance, the current version of the EU taxonomy, which is intended to define the economic activities aligned with a net-zero trajectory by 2050, does not yet classify all activities. Moreover, ECB (2023) published the third review of the disclosure of climate-related and environmental risks among significant institutions and a selected number of less significant institutions, showing that only a limited share of relevant information is disclosed and that the overall quality of available environmental data remains poor.[2] In the same vein, ESMA (2023) documented that between 2020 and 2021 the number of *greenwashing* controversies involving large European firms increased.

In this paper we are interested in analyzing whether and how firms' environmental performance can influence the lending and pricing policies of financial intermediaries. From a bank's perspective, *greenwashing* is particularly relevant because it blurs the assessment of climate-related risks: unreliable sustainability claims could lead to mispricing, distort credit allocation, and expose lenders to reputational and transition risks if firms' true environmental profiles emerge later on. Banks may incorporate climate-related concerns by charging higher interest rates or

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[2]The analysis is mainly based on the European Banking Authority (EBA) Implementing Technical Standards (ITS) on Pillar 3 disclosures on environmental, social and governance (ESG) risks.

restricting credit to companies with higher carbon emissions, but doing so requires distinguishing genuine environmental improvements from mere marketing. These dynamics may also be affected by unexpected monetary policy shocks through the risk-taking channel, potentially altering banks' incentives and ability to screen borrowers. To study such mechanisms, we rely on granular credit data combined with environmental information on both banks and firms, which allows us to capture potential variations in lending relationships depending on the perceived reliability of firms' environmental profiles.

A novel aspect of our approach is the use of web-scraping and text-analysis techniques to assess the credibility of firms' environmental reporting. While traditional measures of *greenwashing* focus on the gap between disclosed information and actual outcomes, here we broaden the perspective by developing indicators of reliability in their public narratives. Company websites represent a primary channel of external communication. By comparing the unstructured qualitative information they contain with the sentiment conveyed in newspaper articles, we obtain a text-based measure of reliability that captures potential discrepancies between firms' self-portrayal and their external image.

The contribution of the paper is twofold. First, it connects to the literature on climate risks, lending practices, and monetary policy by analyzing how the perceived reliability of firms' environmental profiles affects credit conditions, an issue so far largely unexplored, especially in the euro area. Second, it proposes new indicators of reliability that can serve as proxies for *greenwashing*, including measures based on textual information. In doing so, the paper contributes to the growing literature on text-analysis techniques, which are increasingly employed to define companies' sustainability profiles and assess their transparency across multiple information sources.

The remainder of the paper is structured as follows. The next section reviews the emerging literature on *greenwashing*, reliability, and their impact on bank–firm relationships. section 3 describes the construction of our multi-source dataset, which combines traditional databases with automated web-scraping and textual data extraction. section 4 outlines our econometric strategy and presents the main findings. Finally, section 5 concludes.

2 Literature Review

The literature relevant to our study can be grouped into three main strands. The first examines the role of banks, lending policies, and monetary policy in addressing climate risks. The second focuses on the definition of *greenwashing*, particularly as it relates to firms' environmental disclosures. The third explores the use of textual data and text-mining techniques to analyze climate-related disclosures and perceptions.

A large body of work highlights how financial and banking systems play a pivotal role in shaping the interactions among climate change, credit, and economic dynamics. As the primary suppliers of credit, banks can channel resources toward either *green* or *brown* investments through their lending decisions, while simultaneously being exposed to climate shocks affecting borrowers (Lamperti et al., 2021).[3] The effectiveness of the credit channel in driving firms' transition plans depends on several factors (Angelini, 2022), and empirical evidence remains mixed. For instance, Kacperczyk and Peydró (2021) show that firms with higher carbon footprints that previously borrowed from banks committed to carbon neutrality subsequently received less credit. This reduced the economic value of these firms without improving their environmental performance,

[3]Based on the EU taxonomy for sustainable activities and the ECB Securities Holdings Statistics (SHS) database, Alessi and Battiston (2022) show that investors with significant holdings in green activities may nevertheless face substantial exposures to transition risk.

suggesting that banks mainly affect emissions through credit reallocation rather than by extending new loans to brown borrowers. Similarly, Reghezza et al. (2022) provide robust evidence that, following the announcement of the 2015 Paris Agreement, European banks reduced the share of loans to more polluting firms. In the same vein, Aiello (2024) documents that after climate considerations were incorporated into the supervisory activities of the Single Supervisory Mechanism (SSM), directly supervised banks reallocated credit toward less polluting companies. Lending policies supporting green projects are also shaped by banks' environmental preferences and by local subsidies for green investments (Accetturo et al., 2024). Moreover, transparent and accurate disclosure of both banks' and firms' environmental performance can mitigate *greenwashing*, improving the allocation of credit. Using AnaCredit data, Giannetti et al. (2023) show, however, that banks with more extensive environmental disclosures tend to lend relatively more to brown rather than green borrowers. Regarding loan pricing policies, Degryse et al. (2023) show that, following the 2015 Paris Agreement, lower interest rates on loans are observed only when *green* banks lend to *green* borrowers. Using AnaCredit data and controlling for borrowers' credit risk, Altavilla et al. (2023) find that euro area banks charge higher interest rates to firms with greater carbon emissions and lower rates to those committed to reducing them. Both the credit and climate risk premia are affected by contractionary monetary shocks, in line with the risk-taking channel of monetary policy. More recently, Sastry et al. (2024) raise doubts about the effectiveness of banks' voluntary climate commitments in shaping lending practices, showing that banks reduce credit in sectors identified as high-priority for decarbonization but behave no differently from lenders without such commitments. Evidence from credit markets also points to important effects. Using data on U.S. firms from the S&P Trucost database, Attig et al. (2021) find that greater *greenwashing*[4] is associated with lower loan spreads, although banks compensate by charging higher non-price components (e.g., fees), thereby preserving expected returns. Similarly, Cao et al. (2022) show that Chinese firms engaging in *greenwashing* can secure lower debt costs and reduced collateral requirements by strategically using media to enhance public perceptions of their ESG profiles.

Greenwashing strategies may obscure the actual effectiveness of firms' efforts to divest polluting assets. Based on U.S. data, Duchin et al. (2025) find that divestitures of polluting plants following environmental risk incidents allow seller firms to reap disproportionate benefits (such as higher ESG ratings and lower compliance costs) by transferring polluting assets to less monitored companies, without achieving real improvements in aggregate pollution levels. Among the main drivers of *greenwashing*, the foundational paper by Delmas and Burbano (2011) argue that limited information about firms' environmental performance and uncertainty regarding regulatory consequences contribute to the spread of this phenomenon. They define *greenwashing* as the practice of communicating positively about environmental performance when it is in fact negative.[5] The likelihood of *greenwashing* can be shaped by firm-specific characteristics. Using sustainability disclosures from the Standard & Poor's top 100 companies, Ruiz-Blanco et al. (2022) show that firms operating in environmentally sensitive industries and those issuing sustainability reports tend to *greenwash*[6] less than peers in other sectors. More recently, Chen and Dagestani (2023) highlight the importance of board composition in shaping the relationship between *greenwashing* and firm value. In recent years, governments and regulators have sought

[4]In Attig et al. (2021), *greenwashing* is defined as the difference between a firm's Effective Concealment Rate and Absolute Concealment Rate, capturing the extent to which the firm discloses symbolic, benign information while concealing more substantive, negative environmental information, thereby creating a misleadingly positive impression of its performance.

[5]Classifying firms along the two dimensions of communicated and actual environmental performance, they identify four categories: *greenwashing*, *vocal green*, *silent green*, and *silent brown*.

[6]In this study, *greenwashing* is defined as the gap between a firm's self-declared sustainability commitment and its actual performance as assessed by external reviewers, such as Bloomberg ESG scores.

to mitigate *greenwashing* through both mandatory and voluntary policy interventions, whose effectiveness depends critically on their design and implementation. Battiston et al. (2024) review the potential costs, limitations, and challenges, as well as the benefits, impacts, and opportunities, of the major green financial sector initiatives, with a particular focus on the transmission channels and implementation timelines of green macroprudential policies, green monetary policies, and green public co-funding.[7] At the micro level, Columba et al. (2025) analyze the effects of the introduction of the SFDR on strategies in the European investment funds sector. They find that funds disclosing a commitment to ESG investment reduce their exposure to ESG risk by selling environmentally risky stocks. However, this does not necessarily translate into lower emissions from *brown* firms, as it may simply reduce these firms' market value without changing their behavior. The overall impact of such tools remains uncertain. Zhang (2022) shows that, under the 2016 Green Finance System Construction Guidelines in China, highly polluting manufacturing firms listed on stock exchanges are more likely to engage in *greenwashing*, particularly when facing financial constraints in securing credit for renewable energy innovation. In this respect, Zhang (2024) argues that the use of Artificial Intelligence (AI) can significantly reduce *greenwashing* by improving the accuracy and reliability of ESG rating disclosures.

Finally, a more recent strand of literature employs text mining to analyze climate-related communication and disclosure. Textual data provide a valuable new source of unstructured qualitative information (Gentzkow et al., 2019), increasingly used across diverse fields, including climate change research.[8] Communication on climate change is today primarily conveyed through social and mass media. de Villiers and van Staden (2011) show that companies strategically disclose environmental information on their websites or in annual reports, while Jungmi (2011) finds that climate change organizations mainly rely on their websites for media relations and fundraising purposes. Schmidt et al. (2022) employ web scraping of company websites to classify firms by their self-presentation on sustainability and to investigate *greenwashing* in the U.S. metal industry. Similarly, Engle et al. (2020) study how to dynamically hedge climate change risk in financial portfolios using data obtained through textual analysis of newspapers.[9] Gourier and Mathurin (2024) construct a *greenwashing* index that influences investor decisions and distorts the climate risk premium, exploiting information from the historical archive of the *Wall Street Journal*. Recently, Effrosynidis et al. (2022) released the Climate Change Twitter Dataset, described as "*the most comprehensive dataset to date regarding climate change and human opinions via Twitter*," which includes 15 million tweets from 2006 to 2019.[10] Moreno and Caminero (2022) apply text-mining algorithms to the Task Force on Climate-Related Financial Disclosures (TCFD) recommendations, analyzing a sample of major listed Spanish companies and financial institutions. Accetturo et al. (2024) develop a dictionary of green terms and apply textual techniques to extract information on green investments from the financial statements of Italian firms. Constructing a *green* glossary and assigning polarities also provides the basis

[7] Glavas et al. (2023) propose an alternative conceptual perspective, suggesting that *greenwashing* may, paradoxically, act as an impulse toward more sustainable trajectories.

[8] See Aprigliano et al. (2023) for an application to forecasting Italian economic activity, and Gariano and Viggiano (2022) for an analysis of the discriminating power of Banca d'Italia's In-house Credit Assessment System (ICAS) based on the Dow Jones Factiva database.

[9] Bua et al. (2024) extend the analysis by separately identifying transition and physical risks, while Faccini et al. (2023) extract textual information from Reuters news releases to test whether U.S. stock prices reflect climate change risks.

[10] Cortado and Chalmeta (2016) provide an overview of how companies use social media for Corporate Social Responsibility (CSR) communication, showing that Twitter is more frequently used to share CSR-related information than Facebook, despite the latter offering greater interactivity. Mazza et al. (2022) conduct an exploratory analysis of CSR communication by energy firms on Twitter following the Covid-19 shock, while Astuti et al. (2022) use textual analysis to examine how the pandemic shaped the Italian Twitter community and the topics discussed on the platform.

for creating text-based green sentiment indicators. For instance, Borms et al. (2021) propose a semi-supervised text-mining method based on a Dutch news corpus covering ESG company performance to construct a sentiment indicator, which in many cases anticipates negative variations in ESG scores from external sources.[11]

Our paper contributes at the intersection of these strands. We examine how climate risks and *greenwashing* influence lending conditions and the transmission of monetary policy by introducing a novel text-mining approach to measure and interpret climate-related disclosures. In doing so, we provide new evidence on the effectiveness of textual indicators for capturing banks' responses to environmental risks and assessing the credibility of firms' transition strategies.

3 Data

We construct our dataset by combining multiple sources of information. In particular, we rely on traditional, well-curated sources, such as the ESCB (European System of Central Banks) statistical data, alongside *new* non-traditional sources obtained through textual analysis and web-scraping techniques. Our objective is to develop and validate *greenwashing* indicators and link them to the financial data of firms, banks, and their interrelationships.

3.1 Structured Databases

We leverage detailed, granular information on individual bank loans in the euro area from the ESCB's AnaCredit (AC) database, which contains data on outstanding commercial loans as well as the characteristics of individual lenders and borrowers[12] (including their respective LEI codes, if available) from the ESCB Register of Institutions and Affiliates Data (RIAD). RIAD primarily functions as a mapping tool for different identifiers, enabling us to obtain a complete set of descriptive variables for the agents (that is, location and industry).

From AC, we focus on four key dimensions: outstanding loan amounts, associated interest rates, borrowers' probability of default, and the residual maturities of contracts. It is worth noting that, while the probability of default captures borrowers' credit risk as assessed by banks, it may not fully reflect their exposure to climate-related risks, particularly forward-looking transition and tail risks, which are difficult to quantify and may therefore not yet be incorporated into standard credit risk models.[13]

Additionally, to assess the impact of unexpected monetary policy shocks, we use both the announced and expected values of the interest rate on the ECB's main refinancing operations (MROs), as reported by the ECB Monetary Policy Decisions and ECB Survey of Professional Forecasters, respectively. We use the euro short-term rate (€STR) as the risk-free rate for the euro area: this rate measures the wholesale unsecured overnight borrowing costs of a sample of euro area banks and it is based on the Money Market Statistical Reporting (MMSR).[14]

Environmental and climate-related information on companies is obtained from private commercial data providers. In particular, we use data from ISS-ESG, which includes CO_2 emissions, environmental scores, and other climate metrics. Following Altavilla et al. (2023), we use the

[11] Piñeiro-Chousa et al. (2022) examine the impact of Twitter sentiment on returns in the green bond market.

[12] AnaCredit excludes borrowers' loan positions below EUR 25,000.

[13] The AC framework requires the one-year probability of default to be reported only by banks applying the internal ratings-based (IRB) approach for credit risk. For each period, and for banks not using IRB models, we assume that a borrower's probability of default equals the weighted average of the probabilities reported by IRB banks, with weights corresponding to the outstanding amounts lent to the borrower.

[14] €STR replaced the Euro Overnight Index Average (EONIA) starting 2 October 2019. Before this period we link €STR to EONIA.

previous year's emissions intensity, defined as total (Scope 1 + Scope 2) carbon emissions (CO_2 and CO_2 equivalents) per million EUR of revenue, as a proxy for firms' carbon efficiency per unit of output.[15]

From the same source, we also draw on the *Reported Emissions Trust Metric*, which provides a numerical assessment of the reliability of issuer-reported emissions data. This metric accounts for external verification, consistency across different sources, and the overall stability of reporting over time.[16] Furthermore, we track firms' GHG reduction targets, distinguishing those with any form of target, whether linked to the Science Based Targets initiative (SBTi) or to other issuer-defined frameworks, from those without, irrespective of the target's status (committed, approved, or ambitious).

Banks play a pivotal role in channeling financial resources toward green investments. To signal their commitment to guiding the transition process and to enhance their credibility, they often set greenhouse gas reduction targets or join climate-focused networks and associations, such as the United Nations Environment Programme – Financial Initiative (UNEP FI). Following Giannetti et al. (2023), we define *green banks* as those that have signed the Principles for Responsible Banking (PRB) promoted by UNEP FI, taking into account the date of signature. In this regard, signatory banks are required to periodically publish documents reporting on the implementation of the PRB and to provide impact analyses aimed at defining specific targets.

From the private commercial data provider ORBIS/Bureau van Dijk (which also supplies available LEI codes) we obtain financial information on corporates. Specifically, using data on total assets, revenues, and the number of employees, we construct a measure of firm size. We then link this information to borrowers' industry and country of origin in order to build a metric that allows for the comparison of firms with different emissions within the same sector, location, and size class.[17]

To control for firms' characteristics, we also include: (i) the liquidity ratio, defined as the ratio of current assets net of inventories to current liabilities; (ii) the composition of debt, measured as the share of loans in total debt (including both loans and long-term debt); and (iii) the gearing ratio, defined as the ratio of debt to equity.

Our sample period spans from January 2019 to December 2023. Since our focus is on the financial implications of firms' climate characteristics, we restrict the dataset to the sample reported in ISS-ESG, which covers 1,570 companies. As ISS-ESG data refer to firms' global activities, we consolidate subsidiary-level information to the ultimate parent institution (the holding company), as identified in RIAD, in line with ECB (2024). Table A.1 presents the main descriptive statistics of our variables after merging the datasets, referring to 1,134 unique companies over the entire sample period.

3.2 Textual Data

Text and natural language are rich and complex sources of information that have historically been challenging to exploit and process due to their inherently unstructured nature. Until recently, the large-scale use of textual data in empirical research was constrained by limitations in data

[15]We scale carbon emissions in thousands of tonnes. The Greenhouse Gas (GHG) Protocol classifies emissions into three categories: direct (Scope 1), electricity indirect (Scope 2), and other indirect (Scope 3). GHG emissions include CO_2, CH_4, HFCs, NF_3, SF_6, N_2O, and PFCs, while CO_2e expresses their impact in terms of the equivalent amount of CO_2 that would produce the same warming effect. Conversion uses each gas's global warming potential (GWP) over a standard horizon, usually 100 years.

[16]When this variable is unavailable, we use the *Climate Emissions Estimated Trust*, a numeric indicator of the explanatory power of the model used to estimate Scope 1 and 2 emissions for the firm. A higher value reflects greater accuracy of estimated data.

[17]Firm size is based on the EU Commission Recommendation of 6 May 2003 concerning the definition of micro, small, and medium-sized enterprises (2003/361/EC).

availability, computational capacity, and analytical tools. Over the past decade, however, significant advances have reshaped this landscape. The increasing accessibility of large text collections, the availability of more powerful computing resources capable of processing massive datasets in reasonable time, and the development of sophisticated algorithms for large-scale text analysis have made it possible to systematically extract, process, and interpret textual information.

As a result, textual data are increasingly recognized as a valuable complement to traditional quantitative indicators, offering nuanced insights that can reveal patterns and relationships otherwise difficult to detect. Within the context of our study, we leverage textual data to obtain a deeper understanding of corporate behavior with respect to environmental and sustainability issues. To this end, our empirical strategy draws on two main sources of textual data.

The first source consists of the official websites of the companies in our sample. Websites constitute direct channels through which firms communicate with their stakeholders, providing clear indications of their strategic priorities and public positioning. We began by extracting the list of all Italian companies from the ISS-ESG dataset over the years. We then wrote a Python script that queried Google for each company name and returned the top three search results. This approach allowed us to identify the official website for most companies. In the few cases where this method did not succeed, we searched for the website manually. This process produced a list of 207 companies whose official websites were identified and checked.

We then developed a second Python script using the `BeautifulSoup` library to crawl these websites and download their complete HTML content, following internal links up to three levels deep within the same domain. When this automated approach failed (mostly for technical reasons, e.g. in the case of single-page applications), we turned to Common Crawl, an open-access repository that regularly archives vast portions of the internet. Common Crawl stores petabytes of raw web data, including HTML pages, metadata, and text extracts, collected through periodic crawls of publicly accessible websites. Its datasets are freely available and widely used in research for tasks such as text mining, search engine development, and large-scale content analysis. However, Common Crawl is less suited for projects focused on a restricted number of websites, since accessing a few domains of interest requires downloading and processing very large amounts of data, often including irrelevant content. Moreover, the temporal granularity of the snapshots and the potential incompleteness of some archived websites may limit its reliability for capturing the most up-to-date corporate information. In our case, we therefore relied on Common Crawl only as a complementary source, to obtain the HTML content for those sites that our script was unable to fetch.[18]

The second source of textual data used in our work is Dow Jones Factiva, a subscription-based database that aggregates news content from thousands of global and domestic sources, including newspapers, magazines, and journals. It is widely used in research and business analysis to monitor press coverage, track market trends, and study public and media perceptions of companies.

From Factiva, we retrieved the newspaper articles related to our sample of Italian companies from the four major national newspapers: *Il Corriere della Sera*, *Il Sole 24 Ore*, *La Repubblica*, and *La Stampa*.[19]. Since the information obtained from corporate websites reflects only the current situation and does not include historical content, we restricted our selection to articles published from May 2023 onward, to avoid capturing coverage that might reflect outdated circumstances. We also excluded articles with more than four company taggings to remove generalist pieces.[20] As shown in Table A.2, this procedure resulted in a dataset comprising more

[18]We used the snapshot CC-MAIN-2024-10, the 10th main crawl of 2024.

[19]National newspapers generally publish more articles on domestic firms than on non-domestic ones. According to Accertamenti Diffusione Stampa, excluding daily sports newspapers, in 2023 these four outlets ranked among the top five in terms of total (print and digital) circulation.

[20]Our aim is to focus on the perception of individual companies; generalist articles risk combining comments

than 10,000 articles.

Figure A.1 and Figure A.2 provide an illustrative example of the final outputs from our Python-based data processing pipeline for a generic anonymized firm. In the website dataset, each observation corresponds to a single company, whereas in the newspaper dataset multiple observations (that is, articles) can be associated with the same firm.

3.3 Identification of *greenwashers*

As stated by Delmas and Burbano (2011), *greenwashing* arises when companies portray their environmental performance in overly positive terms while their actual performance is poor. In the following, we aim to capture this behavior by combining two metrics derived from structured and unstructured sources. A further way to assess *greenwashing*, the key intuition behind our empirical setup, is that a firm may claim environmental virtue and therefore report low emissions, yet if such disclosures are not credible, low reported carbon intensity may signal misrepresentation rather than genuine sustainability.

3.3.1 The Structured-based Metric

We first construct a structured-based metric of *greenwashing* using climate information provided by ISS-ESG. Carbon-emission data from ISS-ESG represent firms' *reported* environmental performance, that is, what companies declare about themselves. An indirect signal of *greenwashing* therefore emerges when low reported emissions are accompanied by low assessed credibility in disclosure. Specifically, if a firm is classified as having low climate trust, meaning that the issuer is deemed unreliable in reporting emission data, yet exhibits low reported carbon intensity, we interpret this as a case in which the firm's public environmental profile is likely overstated (upper-left corner of Table A.3). In other words, these firms look *green* on paper because they claim to be so, but their narratives are not considered trustworthy. At the opposite end, firms with high climate trust that openly and accurately report high emissions can be defined as *browntrusters* (bottom-right corner of Table A.3).[21] Between these two extremes, we classify firms as *greentrusters* and *brownwashers*[22] when they are characterized by high/low values of climate trust and carbon-intensity factors, and vice versa, respectively.

Figure A.3 shows the dynamics of the average weighted interest rate by the factors behind the definition of *greenwashing*. By splitting the firms' sample by the median values of the carbon emissions and climate trust variables, we show that charged interest rates are higher for companies experiencing greater carbon intensities and lower assessed reliability in reporting emissions data, respectively. Then, we cannot assess their joint final effect. Similarly, Figure A.4 shows that, on average, the size of the banks' loans granted is greater for companies having lower carbon emissions and higher accuracy in their reporting models, respectively. From an operational point of view, we define *greenwashers* as the companies having both values for the climate trust and the carbon intensity below the median values of their distributions by time, country and industry: Figure A.5 plots the average interest rate and the mean outstanding amounts by *greenwashing* status, showing that the descriptive evidence is inconclusive and that a more in-depth econometric analysis is needed.[23]

on multiple firms (potentially of a different nature) or discussing broader environmental trends, making sentiment classification substantially more complex.

[21] We are implicitly assuming that misreporting, when present, is more likely to bias reported emissions downward, in favour of the issuer.

[22] In particular, *brownwashing* arises when companies tend to understate their poor environmental performance because of limited reporting capabilities.

[23] The swings in the average loans' amounts reported in Figure A.4 and Figure A.5 are mainly due to the

3.3.2 The Text-based Metric

Text and sentiment analysis can be conducted using many different methods. Among these, the Bag-of-Words (BoW) and embedding-based approaches are probably the most widely used. In the BoW framework, text is represented as a collection of words or fixed-length sequences (n-grams), disregarding grammar and word order but retaining frequency information. Techniques such as the dictionary approach, term frequency-inverse document frequency (TF-IDF), and supervised classifiers can be applied within this framework. Embedding-based approaches, by contrast, map words, phrases, or documents into dense vector spaces that capture semantic and contextual relationships, as in Word2Vec, GloVe, BERT, or other large language models.[24]

For this study, we adopted the dictionary approach, a variant of BoW, as it offers transparency, interpretability, and full control over classification criteria.[25] Following Accetturo et al. (2024), we compiled two dictionaries: a green dictionary containing climate change-related terms (unigrams) and multi-word expressions (n-grams), and a separate dictionary of valence shifters. Each term in the green dictionary was assigned a polarity[26] to indicate its sentiment orientation, while the valence shifter dictionary specified modifiers affecting the intensity or direction of that sentiment. The dictionaries included Italian terms and their English translations (see Table A.6 and Table A.7). To implement the dictionary matching, we developed an algorithm based on a trie (prefix tree) data structure. This allows efficient detection of both unigrams and multi-word expressions, while also accounting for valence shifters that modify the polarity of subsequent terms. At each token position, the algorithm searches for the longest dictionary match and, if a valence shifter is found within the preceding context, adjusts the score accordingly. This ensures fast look-up, consistent handling of multi-word expressions, and accurate integration of context-dependent sentiment adjustments. To ensure consistent processing and accurate matching, both website and media texts, as well as the entries in both dictionaries, were lemmatized and tokenized.[27]

In this way, we were able to compute a sentiment score for each company, separately for website content and for media articles, with descriptive statistics reported in Table A.8. This separation enabled a direct comparison between the sentiment expressed in a company's own communications and that conveyed in media coverage, without making prior assumptions about the nature or extent of any differences.

In the spirit of Aprigliano et al. (2023), for each company f, we constructed an Average Sentiment Indicator (ASI) by averaging the sentiment scores of all articles computed with our green dictionary. Let N denote the number of articles, L the number of tokens in a given article j, and i the index of a term. The sentiment score indicator for Factiva articles is computed as:

$$\overline{ASI}_f^{\text{art}} = \frac{\Sigma_j^N \left(\Sigma_i \frac{P_i \cdot VS(i)}{L_j} \right)}{N} \tag{1}$$

where P_i and $VS(i)$ represent, respectively, the polarity and the valence shifter associated with term i.

Similarly, the sentiment indicator based on a company's website is given by:

increase in the number of observations and the relative mean amount in 2022 with respect to the previous and following years (see also Table A.4). Further descriptive statistics on *greenwashers* are reported in Table A.5.

[24] For an overview of the different approaches to text analysis, see Marcucci (2024).

[25] The choice was also shaped by practical considerations: due to contractual terms with Factiva, we were not allowed to process the newspaper dataset using large language models, which limited the choice of methods.

[26] At this stage, neutral concepts with polarity equal to zero were excluded.

[27] Lemmatization reduces words to their canonical forms, while tokenization splits the text into individual units, or tokens.

$$\overline{ASI}_f^{\text{web}} = \Sigma_i \frac{P_i \cdot VS(i)}{L_f}. \tag{2}$$

We validated the sentiment scoring procedure using two complementary approaches. First, we tested it on texts automatically generated by large language models (LLMs) to mimic a broad range of positive and negative statements on environmental sustainability, confirming that the method captured expected variations in sentiment intensity. Second, for company websites, we compared our results with scores obtained from Google's Gemini 2.5-Flash-Lite. To this end, we developed a dedicated Python script that uses the Google API to pass the text extracted from each website directly to Gemini. Since each prompt refers to a specific piece of text, it was not possible to build a continuous measure comparable to our Average Sentiment Indicator. Instead, in our script Gemini provides a discrete classification of sentiment, assigning each website a profile ranging from +2 (strongly positive) to –2 (strongly negative). The two measures (our ASI and Gemini's scores) showed a positive correlation above 0.5, which is consistent with methodological differences: our indicator is continuous, while Gemini's is discrete, and in our framework longer texts tend to yield slightly lower intensities due to token-count normalization. Taken together, these tests provide reassuring evidence on the reliability and robustness of our sentiment scoring methodology.

For a first analysis of our results, we defined:

$$\Delta_f^{\text{sent}} = \overline{ASI}_f^{\text{art}} - \overline{ASI}_f^{\text{web}}$$

as the difference between the average sentiment scores from media coverage and from company websites. Negative values of Δ_f^{sent} indicate that website sentiment is more positive than media sentiment, suggesting that firms tend to present themselves more favorably through their own communication channels. Indeed, Figure A.6 shows that the median sentiment score based on website content is higher than that derived from Factiva articles. This difference is statistically significant, as confirmed by a test of the difference in sample means (Table A.9).

To identify potential greenwashers using text data, we followed the general approach outlined in Subsection 3.3.1. Specifically, we classified as greenwashers those firms that report *low carbon emissions* (that is, a reported carbon intensity sourced from ISS-ESG below the median by two-digit NACE Rev.2 sector, country, and reporting date), while at the same time exhibiting *low credibility*. Credibility could be assessed through Δ_f^{sent}, by flagging as *less credible* firms with below-median values of Δ_f^{sent}. However, in order to isolate more clear-cut cases of misalignment between self-disclosure and external perception, we adopted a more restrictive definition.

In particular, we defined robustly standardized average sentiment indicators from company websites and newspaper articles, using the median and the median absolute deviation (MAD) as reference measures.[28] Following the notation introduced in Equations (1) and (2), we defined the standardized indicators as:

$$s_f^{\text{web}} = \frac{\overline{ASI}_f^{\text{web}} - \text{median}\left(\overline{ASI}_f^{\text{web}}\right)}{\text{MAD}_{\text{web}}} \qquad s_f^{\text{art}} = \frac{\overline{ASI}_f^{\text{art}} - \text{median}\left(\overline{ASI}_f^{\text{art}}\right)}{\text{MAD}_{\text{art}}}$$

where

$$\text{MAD}_{\text{web}} = \text{median}\left(\left|\overline{ASI}_f^{\text{web}} - \text{median}\left(\overline{ASI}_f^{\text{web}}\right)\right|\right)$$

[28] This approach yields standardized scores that express each firm's deviation from the median in units of MAD, making the measure less sensitive to outliers and skewed distributions.

and an analogous definition applies to $\mathrm{MAD}_{\mathrm{art}}$. A firm is flagged as having low credibility when its standardized website sentiment exceeds 1, indicating an unusually positive self-disclosure, while its standardized article sentiment falls below 0, reflecting a negative media portrayal:

$$\mathrm{TR}_{\mathrm{txt}} = \begin{cases} 1 & \text{if } s_f^{\mathrm{web}} > 1 \text{ and } s_f^{\mathrm{art}} < 0, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

Applying this procedure, we identified 12 low-credibility firms out of the 86 Italian companies resulting from the merge of ISS-ESG, AnaCredit, and text datasets. If, in a given reference period, a firm also satisfies the low-emissions condition, it is classified as a potential greenwasher. For instance, as of December 2023, this condition was met by 3 companies; notably, all of them had also been identified by the ISS-ESG-based metric.

In any case, our aim is not to construct an alternative reliability indicator to replace the information provided by ISS, but rather to develop a complementary tool. The ISS trust metric, in fact, focuses mainly on the consistency and quality of corporate data reporting, taking into account whether the issuer reported data has been externally verified, the extent of discrepancies between information reported to different sources, and the coherence of reporting over time. The textual indicators we have developed rest on different premises and capture complementary aspects of corporate communication. In particular, instead of focusing on the formal reporting of quantitative data, they emphasize the content and tone of firms' public communication. For this reason, we address our analysis to the subset of firms identified as potential greenwashers according to both structured ISS data and our textual indicators.

In our opinion, this strategy provides a useful refinement of the greenwashing identification process. Relying solely on the ISS metric risks producing too broad a set of suspect cases, potentially capturing firms whose inconsistencies are due merely to reporting practices rather than deliberate opportunism. By contrast, the combined use of textual and structured measures narrows the focus to firms that simultaneously exhibit inconsistencies in formal reporting and misalignments in public communication, thereby offering a stronger basis for identifying genuine greenwashing behavior.

4 Main results

In this section, we present several panel regressions that account for time, borrower, and bank characteristics in order to derive implications for the relationship between banking policies and climate information, as well as to capture the effects of monetary policy shocks. In this context, as anticipated in the previous sections, our main focus is on understanding the role of *greenwashing*.

4.1 Banking policies and structured climate information

In this section, we investigate the effects of firms' climate profiles on banks' policies by addressing the following research question: does *greenwashing* enable companies to obtain cheaper and greater access to bank credit?

When analyzing *pricing policies*, our dependent variable $s_{f,b,t}$ is defined as the weighted average interest rate applied by bank b to firm f at time t. For *loan volumes*, $s_{f,b,t}$ represents the symmetric quarterly growth rate of loans granted by bank b to firm f at time t, defined as

$$\frac{OA_t - OA_{t-3}}{0.5 \times (OA_t + OA_{t-3})},$$

where OA denotes outstanding amounts.[29] This transformation provides a second-order approximation of the log-difference growth rate around zero, bounding the distribution between -2 and 2 and capturing both extensive and intensive margin variations.[30]

We first consider the following panel regression model:

$$s_{f,b,t} = \beta_1 PD_{f,b,t} + \beta_2 CI_{f,t} + \beta_3 CT_{f,t} + \beta_4 \left(CI_{f,t} \times CT_{f,t}\right) + \theta_{f,b,t} + \varepsilon_{f,b,t} \tag{4}$$

where we regress s on the probability of default (PD), carbon intensity (CI), and climate trust (CT) of companies. The vector θ incorporates fixed effects. For each specification, we estimate a version with separate bank and time fixed effects (capturing bank-specific and cyclical factors) and another with bank time-varying fixed effects.[31] Since the coefficients of interest are defined at the firm level, firm time-varying fixed effects cannot be included. Following Degryse et al. (2019), we include the time-varying combination of firm' industry (NACE Rev. 2 classification), geographical location, and size class (ILS). Finally, we add time-varying fixed effects related to loans' residual maturity buckets, accounting for interest rates on lending relationships of similar average maturity.[32]

Table 1 summarizes the results for Equation 4. Columns 1–4 and 5–8 present evidence on pricing and loan volumes, respectively.[33] Columns 1 and 2 report the estimation of Equation 4 without interactions among variables CI and CT. The first column includes separate time and bank fixed effects, while the second considers their interaction; in both cases, all coefficients are statistically significant. Consistent with Altavilla et al. (2023), the coefficient β_1 is positive, indicating that borrowers with a higher probability of default face higher interest rates. Corporates with greater carbon intensity are also charged higher loan prices (β_2), while firms with higher assessed reliability in reporting emissions data benefit from more favorable pricing conditions (β_3 negative). In column 3, the coefficient β_4 is negative but not statistically significant, suggesting little evidence that greater confidence in firms' climate reporting leads to lower interest rates when emission levels are high. These results are robust to the inclusion of bank time-varying fixed effects (column 4).

In columns 5 to 8, we replace the dependent variable to study loan volumes granted by euro area banks. As expected, riskier companies obtain less credit (β_1 is always negative and significant). Across all specifications, companies with higher assessed reliability in their reporting borrow more credit than firms with lower climate trust scores (β_3). In specifications 7 and 8, which include both base and interaction effects for carbon intensity and climate trust, we find that more polluting firms (β_2) receive less credit, unless they demonstrate higher reliability in reporting emissions data (β_4).

The interaction coefficient in Equation 4 captures only the average joint effect of carbon intensity and climate trust across firms, and therefore cannot be used to directly identify which firms engage in *greenwashing*. As explained above, using the same two variables we can classify firms into four mutually exclusive categories. *Greenwashers* are firms whose climate trust and carbon intensity are both below the median values of their distributions (by time, country, and industry), which implies an overstated public environmental profile. *Brownwashers* are

[29]Similar results are obtained when using annual variations.

[30]See Dell'Ariccia and Garibaldi (2005) and Accetturo et al. (2024) for applications in the credit market.

[31]In all tables, we test whether separate bank and time fixed effects yield different results compared to bank time-varying fixed effects.

[32]Residual maturity classes: up to 1 year; over 1 and up to 5 years; over 5 and up to 10 years; and over 10 years. Similar results are obtained using original maturity buckets.

[33]Bottero and Cascarano (2024) show that banking sector profitability depends on both price and quantity effects. They find that banks apply a discount to the cost of credit for firms that unexpectedly reduce emissions. This reduces sectoral margins, which can be offset by increasing lending to non-granular sectors characterized by large sustainable investments.

Table 1: Bank lending and climate information

	Weighted average interest rate			
	[1]	[2]	[3]	[4]
PD	0.0140***	0.0108***	0.0140***	0.0108***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
CI	0.0011***	0.0011***	0.0013***	0.0012***
	(0.0001)	(0.0001)	(0.0003)	(0.0003)
CT	-0.0014***	-0.0020***	-0.0014***	-0.0020***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
CI x CT			-0.0003	-0.0002
			(0.0003)	(0.0003)
Time FE	Yes	No	Yes	No
Bank FE	Yes	No	Yes	No
Bank x Time FE	No	Yes	No	Yes
ILS x Time FE	Yes	Yes	Yes	Yes
Mat. x Time FE	Yes	Yes	Yes	Yes
N	622,531	596,958	622,531	596,958

	Symmetric quarterly loans' growth rate			
	[5]	[6]	[7]	[8]
PD	-0.0875***	-0.0846***	-0.0873***	-0.0844***
	(0.0116)	(0.0117)	(0.0116)	(0.0117)
CI	-0.0009	-0.0032	-0.0263**	-0.0344***
	(0.0021)	(0.0022)	(0.0108)	(0.0123)
CT	0.0341***	0.0336***	0.0313***	0.0302***
	(0.0111)	(0.0116)	(0.0112)	(0.0116)
CI x CT			0.0333**	0.0408**
			(0.0146)	(0.0164)
Time FE	Yes	No	Yes	No
Bank FE	Yes	No	Yes	No
Bank x Time FE	No	Yes	No	Yes
ILS x Time FE	Yes	Yes	Yes	Yes
Mat. x Time FE	Yes	Yes	Yes	Yes
N	556,167	532,191	556,167	532,191

[1] *Note*: Standard errors are clustered at time-varying bank level.
[2] Standard errors in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

firms with above-median carbon intensity and below-median climate trust. *Browntrusters* have above-median carbon intensity and climate trust, while *Greentrusters* have below-median carbon intensity and above-median climate trust.

Accordingly, Equation 5 refines the previous specification by replacing the $CI \times CT$ interaction term with our proxies for *greenwashers* GW, *browntrusters* BT, and *greentrusters* GT, introduced in Subsection 3.3.1. We omit *brownwashers* as the reference category to avoid perfect multicollinearity.

$$s_{f,b,t} = \beta_1 PD_{f,b,t} + \beta_2 CI_{f,t} + \beta_3 CT_{f,t} + \beta_4^{GW} GW_{f,t} + \beta_4^{BT} BT_{f,t} + \beta_4^{GT} GT_{f,t} + \theta_{f,b,t} + \varepsilon_{f,b,t} \quad (5)$$

Results are reported in Table 2, where the coefficients of primary interest are those associated with the firm climate-profile indicators (the β_4 terms). The estimated effects of PD and (when included) CI are broadly consistent with those in Table 1, while the coefficient on CT becomes smaller and generally loses statistical significance.

Turning to the climate-profile indicators, the coefficients on GW, BT, and GT are negative and statistically significant in columns 1 to 6, indicating that these borrower types obtain lower interest rates relative to *brownwashers*. While it is not surprising that the baseline group faces worse terms, the comparison across categories is indeed informative. In particular, *greentrusters* (GT) receive a larger discount than *greenwashers* (GW), highlighting the role of transparency: conditional on low reported carbon intensity, higher credibility in emissions reporting is associated with more favorable pricing. At the same time, *greenwashers* still obtain a larger discount than *browntrusters* (BT), suggesting that reported emissions also matter: *appearing* green in reported carbon intensity is associated with better loan pricing even when disclosure credibility is lower.

However, as detailed in subsection 3.1, the climate trust indicator used in columns 1 and 2 combines information on *reported* emissions with an assessment based on *estimated* emissions when firms do not report. A concern is therefore that the results may be driven by the estimated-emissions component. To address this, in columns 3 and 4 we use only the *Reported Emissions Trust Metric*. Although this reduces the sample by about 70,000 observations, the results remain fully consistent.

Another concern is that jointly including CI and CT together with the category indicators (GW, GT, and BT) could introduce mechanical correlation, since the group dummies are constructed from carbon intensity and disclosure trust. For this reason, columns 5 and 6 drop CI and CT from the regressors; the estimated coefficients on the group indicators remain essentially unchanged.

Finally, columns 7 and 8 focus exclusively on our main proxy of interest, GW. Our goal is not to rank all firm profiles, but to test and quantify the specific contribution of *greenwashing* to differential bank pricing. For this reason, we adopt a specification with a single indicator (GW), which better isolates the group of interest and compares it to all other firms; we retain this specification for the remainder of the paper. Under this broader reference category (which now also includes *greentrusters*), the coefficient on GW remains negative and statistically significant, though smaller in magnitude than in columns 1–6, as expected.

Turning to loan growth (columns 9 to 16 in Table 2), credit risk (PD) remains a key determinant of lending dynamics: its coefficient is negative and highly significant across all specifications, indicating that riskier borrowers experience lower subsequent loan growth. By contrast, the coefficients on CI and CT are generally small and not robustly significant across specifications.

The climate-profile indicators point to meaningful heterogeneity across firm types. *Browntrusters* (BT) display systematically higher loan growth (positive and strongly significant in

Table 2: Bank lending and *greenwashing* (1)

	Weighted average interest rate							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
PD	0.0136***	0.0103***	0.0191***	0.0164***	0.0191***	0.0164***	0.0197***	0.0170***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
CI	0.0010***	0.0010***	0.0009***	0.0008***				
	(0.0001)	(0.0001)	(0.0001)	(0.0001)				
CT	-0.0001	-0.0005**	0.0000	-0.0003				
	(0.0002)	(0.0002)	(0.0002)	(0.0002)				
BT	-0.0007***	-0.0008***	-0.0007***	-0.0007***	-0.0006***	-0.0007***		
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)		
GW	-0.0011***	-0.0012***	-0.0010***	-0.0010***	-0.0010***	-0.0011***	-0.0004***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GT	-0.0013***	-0.0015***	-0.0016***	-0.0017***	-0.0016***	-0.0018***		
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)		
Time FE	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	No	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes	No	Yes
ILS×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mat.×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	622,531	596,958	553,811	528,305	553,811	528,305	553,811	528,305

	Symmetric quarterly loans' growth rate							
	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
PD	-0.0864***	-0.0831***	-0.0759***	-0.0676***	-0.0760***	-0.0676***	-0.0783***	-0.0707***
	(0.0116)	(0.0117)	(0.0149)	(0.0154)	(0.0148)	(0.0154)	(0.0149)	(0.0154)
CI	-0.0018	-0.0039*	0.0020	0.0000				
	(0.0021)	(0.0022)	(0.0042)	(0.0044)				
CT	-0.0027	-0.0018	0.0017	-0.0051				
	(0.0133)	(0.0138)	(0.0145)	(0.0152)				
BT	0.0163***	0.0144***	0.0138***	0.0133***	0.0142***	0.0126***		
	(0.0044)	(0.0046)	(0.0048)	(0.0051)	(0.0043)	(0.0045)		
GW	-0.0040	-0.0030	-0.0025	-0.0015	-0.0026	-0.0015	-0.0089**	-0.0080**
	(0.0035)	(0.0037)	(0.0040)	(0.0042)	(0.0040)	(0.0042)	(0.0035)	(0.0037)
GT	0.0082*	0.0097**	0.0048	0.0080	0.0049	0.0073*		
	(0.0043)	(0.0045)	(0.0048)	(0.0050)	(0.0042)	(0.0044)		
Time FE	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	No	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes	No	Yes
ILS×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mat.×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	556,167	532,191	499,203	475,290	499,203	475,290	499,203	475,290

Note: Standard errors are clustered at the (time-varying) bank level.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

columns 9 to 14). One interpretation could be that high-emission but credible firms are undertaking transition plans and therefore demand (and obtain) more credit to finance related investments. *Greentrusters* (GT) also show positive loan growth where included, although statistical significance is less stable across columns. The coefficient on *greenwashers* (GW) is negative throughout and becomes statistically significant in the specifications that focus on the GW indicator only (columns 15 and 16). Overall, the loan-growth evidence suggests that disclosure credibility plays a more prominent role on the credit-expansion margin, with higher-trust firms exhibiting stronger credit growth.

Overall, these results suggest that being identified as a (potential) greenwasher does not translate into more favorable outcomes in credit quantities; if anything, banks appear to restrict credit growth to greenwashers while still offering lower interest rates in the pricing regressions. This pattern suggests that banks may differentiate along both the price and quantity margins.

In Table 3, we extend the analysis in Table 2 by adding further firm-level controls to better isolate the marginal effect of our greenwashing proxy and to mitigate concerns that the baseline associations may be driven by other firm characteristics. Moreover, as noted above, from this point onward our analysis no longer includes Climate Trust and Carbon Emissions as separate explanatory variables, nor does it retain the full set of environmental-profile proxies. We therefore keep from the previous model only PD and our main proxy of interest, GW. In columns 1 and 2, we add firm fixed effects; coefficients β_1 and β_4 remain consistent with previous results. To capture potentially unobserved demand drivers and avoid confounding effects, columns 3 and 4 incorporate time-varying borrower and lending relationship characteristics. On the firm side, we include the liquidity ratio (LR), the debt composition ($COMP$), the gearing ratio ($GEAR$), and the presence of a GHG reduction target (FT). On the relationship side, we consider the duration of the bank–firm relationship (DUR) and the share of loans provided by a bank to a given firm ($SHARE$). Finally, we control for GB, an indicator identifying "green banks" subscribed to UNEP initiatives. The equation now becomes:

$$\begin{aligned} s_{f,b,t} =& \beta_1 PD_{f,b,t} + \beta_4 GW_{f,t} + \beta_5 LR_{f,t} + \beta_6 COMP_{f,t} + \beta_7 GEAR_{f,t} + \beta_8 DUR_{f,b,t} \\ &+ \beta_9 SHARE_{f,b,t} + \beta_{10} FT_{f,t} + \beta_{11} GB_{b,t} + \beta_{12} \left(GW_{f,t} \times GB_{b,t}\right) + \beta_{13} \left(FT_{f,t} \times GB_{b,t}\right) \\ &+ \theta_{f,b,t} + \varepsilon_{f,b,t} \end{aligned} \tag{6}$$

Although including these variables reduces the sample size by about half, the main results remain unchanged. Firm-level controls behave as expected: more liquid or better-capitalized firms obtain lower interest rates, while longer and more concentrated lending relationships also benefit from reduced loan pricing. Turning to environmental variables, our findings align with Altavilla et al. (2023). The coefficient on FT is negative and statistically significant, showing that banks incorporate firms' climate strategies when assessing risk and reward lower interest rates to those with a GHG reduction target. The coefficient on GB suggests that green banks charge higher interest rates unless borrowers disclose emission reduction plans (β_{13}). No significant effects are found for the interaction between GW and GB in most specifications.

To address potential reverse causality between the definition of *greenwashers* and credit dynamics, columns 5 and 6 test robustness using a predetermined *greenwashing* proxy based on the classification at the end of 2018, fixed over the sample period. Results confirm our main findings: we find strong evidence that *greenwashers* borrow at lower costs than other firms. Across specifications, *greenwashers* achieve interest rate reductions of 3 to 7 basis points.

Columns 7 to 12 of Table 3 replicate the specifications using loan growth as the dependent variable. While most results are confirmed and the effects of FT and GB align with expectations,

Table 3: Bank lending and *greenwashing* (2)

	Weighted average interest rate						Symmetric quarterly loans' growth rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
PD	0.0046***	0.0032***	0.0023***	0.0024***	0.0025***	0.0025***	-0.0225	-0.0062	-0.0943***	-0.1028***	-0.0892***	-0.0982*
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0236)	(0.0239)	(0.0193)	(0.0196)	(0.0195)	(0.0198
GW	-0.0003***	-0.0003***	-0.0003***	-0.0005***	-0.0006***	-0.0004***	0.0101*	0.0103*	-0.0016	0.0034	-0.0094**	-0.0079*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0053)	(0.0057)	(0.0043)	(0.0046)	(0.0040)	(0.0042
LR			-0.0004***	-0.0003***	-0.0005***	-0.0003***			-0.0016	-0.0015	-0.0022	-0.0020
			(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0016)	(0.0017)	(0.0016)	(0.0017
COMP			-0.0041***	-0.0040***	-0.0041***	-0.0040***			-0.0385***	-0.0313**	-0.0378***	-0.0308*
			(0.0002)	(0.0002)	(0.0002)	(0.0002)			(0.0118)	(0.0125)	(0.0118)	(0.0125
GEAR			0.0000***	0.0000***	0.0000***	0.0000***			-0.0000	-0.0000	-0.0000*	-0.0000*
			(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0000)	(0.0000)	(0.0000)	(0.0000
DUR			-0.0003***	-0.0003***	-0.0003***	-0.0003***			-0.0152***	-0.0170***	-0.0152***	-0.0170*
			(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0013)	(0.0017)	(0.0013)	(0.0017
SHARE			-0.0024***	-0.0042***	-0.0025***	-0.0042***			0.2043***	0.3713***	0.2034***	0.3687*
			(0.0002)	(0.0003)	(0.0002)	(0.0003)			(0.0098)	(0.0150)	(0.0098)	(0.0150
FT			-0.0012***	-0.0010***	-0.0012***	-0.0010***			0.0226***	0.0191***	0.0220***	0.0192*
			(0.0001)	(0.0001)	(0.0001)	(0.0001)			(0.0057)	(0.0060)	(0.0056)	(0.0060
GB			0.0016***		0.0016***				-0.0250*		-0.0244*	
			(0.0002)		(0.0002)				(0.0135)		(0.0135)	
GW x GB			-0.0002	0.0003	0.0005***	0.0001			0.0094	0.0079	-0.0040	-0.0005
			(0.0002)	(0.0002)	(0.0002)	(0.0001)			(0.0100)	(0.0102)	(0.0084)	(0.0087
FT x GB			-0.0004**	-0.0013***	-0.0004**	-0.0013***			0.0183	0.0236**	0.0177	0.0231*
			(0.0002)	(0.0002)	(0.0002)	(0.0002)			(0.0112)	(0.0116)	(0.0112)	(0.0116
Time FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Bank x Time FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
ILS x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	No	No	Yes	Yes	No	No	No	No
Mat. x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	553,792	528,283	281,473	264,611	281,473	264,611	499,191	475,276	254,514	238,635	254,514	238,635

[1] *Note*: Standard errors are clustered at time-varying bank level.
[2] Standard errors in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

the coefficients related to greenwashing do not display clear or robust statistical significance in terms of credit quantity, particularly when firm-level characteristics are included.

Finally, in Table 4 we replicate the regressions including firm and relationship characteristics, this time allowing for interactions between GW and $NACE$ sectors in order to identify industries that benefit most from *greenwashing*. This specification requires replacing time-varying Industry–Location–Size (ILS) fixed effects with only Location–Size fixed effects. The equation is now:

$$\begin{aligned} s_{f,b,t} =& \beta_1 PD_{f,b,t} + \beta_4 GW_{f,t} + \beta_4^N NACE_{f,t} + \beta_4^{GN} \left(GW_{f,t} \times NACE_{f,t} \right) + \beta_5 LR_{f,t} \\ &+ \beta_6 COMP_{f,t} + \beta_7 GEAR_{f,t} + \beta_8 DUR_{f,b,t} + \beta_9 SHARE_{f,b,t} + \beta_{10} FT_{f,t} + \beta_{11} GB_{b,t} \\ &+ \beta_{12} \left(GW_{f,t} \times GB_{b,t} \right) + \beta_{13} \left(FT_{f,t} \times GB_{b,t} \right) + \theta_{f,b,t} + \varepsilon_{f,b,t} \end{aligned} \tag{7}$$

Table 4: Bank lending and the interacted effect of *greenwashing* by sector of economic activity

	Weighted average interest rate		Quarterly loans' growth rate	
GW × ...	[1]	[2]	[3]	[4]
B - Mining and quarrying	-0.0016***	-0.0002	0.1048***	0.1062***
	(0.0004)	(0.0005)	(0.0224)	(0.0241)
C - Manufacturing	0.0009***	0.0010***	0.0671***	0.0660***
	(0.0002)	(0.0002)	(0.0130)	(0.0140)
D - Electricity, gas, steam and air conditioning supply	0.0029***	0.0036***	0.0822***	0.0717**
	(0.0005)	(0.0005)	(0.0279)	(0.0297)
E - Water supply; sewerage, waste management and remediation activities	-0.0002	0.0020	-0.2565**	-0.1815
	(0.0015)	(0.0014)	(0.1306)	(0.1249)
F - Construction	0.0049***	0.0051***	0.1616***	0.1627***
	(0.0004)	(0.0004)	(0.0253)	(0.0274)
G - Wholesale/retail trade; repair of motor vehicles and motorcycles	-0.0010***	-0.0011***	0.1429***	0.1211***
	(0.0004)	(0.0004)	(0.0242)	(0.0249)
H - Transportation and storage	0.0033***	0.0036***	0.0611***	0.0630***
	(0.0002)	(0.0002)	(0.0132)	(0.0142)
I - Accommodation and food service activities	0.0009*	0.0019***	0.0749***	0.0449
	(0.0005)	(0.0006)	(0.0255)	(0.0275)
J - Information and communication	-0.0009***	-0.0012***	0.0545***	0.0508**
	(0.0003)	(0.0003)	(0.0189)	(0.0203)
K - Financial and insurance activities	0.0031***	0.0029***	0.0241	0.0198
	(0.0005)	(0.0005)	(0.0283)	(0.0311)
L - Real estate activities	0.0002	0.0026***	0.1329***	0.1207**
	(0.0008)	(0.0007)	(0.0492)	(0.0488)
M - Professional, scientific and technical activities	0.0031***	0.0039***	0.0197	0.0138
	(0.0003)	(0.0003)	(0.0212)	(0.0225)
N - Administrative and support service activities	0.0058***	0.0082***	0.2066	0.2408
	(0.0021)	(0.0022)	(0.1661)	(0.1676)
O - Public administration and defense; compulsory social security	-0.0042	-0.0040	-0.4930***	-0.5590***
	(0.0039)	(0.0035)	(0.1870)	(0.1744)
Q - Human health and social work activities	0.0025***	0.0022***	0.0492**	0.0751***
	(0.0008)	(0.0007)	(0.0238)	(0.0254)
R - Arts, entertainment and recreation	-0.0014*	-0.0004	0.0801*	0.0704
	(0.0008)	(0.0009)	(0.0457)	(0.0481)
S - Other service activities	-0.0134***	-0.0119***	0.0804	-0.1329***
	(0.0008)	(0.0004)	(0.0645)	(0.0340)
Time FE	Yes	No	Yes	No
Bank FE	Yes	No	Yes	No
Bank x Time FE	No	Yes	No	Yes
Location-Size x Time FE	Yes	Yes	Yes	Yes
Mat. x Time FE	Yes	Yes	Yes	Yes
N	223,000	210,184	198,712	186,800

[1] *Note*: Standard errors are clustered at time-varying bank level.
[2] Standard errors in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

Our analysis mainly focuses on the coefficients on $GW \times NACE$ (β_4^{GN}). Since Section A (Agriculture, Forestry and Fishing) is the omitted category, each interaction coefficient captures the *difference* in the GW effect in sector k relative to Section A.

For loan pricing (columns 1 and 2), the results highlight substantial cross-industry heterogeneity: some sectors feature significantly more favorable pricing for suspected greenwashers than the baseline (e.g., negative and significant differentials in Mining and quarrying and in Wholesale/retail trade), whereas other sectors display a significantly weaker discount or a relative penalty (e.g., positive and significant differentials in Construction, Utilities, Transport, and several service industries). Notably, several of the sectors for which the GW differentials are statistically significant are also typically among the most polluting segments of the economy, in particular energy and utilities (electricity and heat generation), industry (including mining and manufacturing), and transport, which are consistently identified as major contributors to greenhouse-gas emissions.

For loan quantities (columns 3 and 4), the evidence is likewise heterogeneous: greenwashers' loan growth is significantly higher than the baseline in many sectors, but significantly lower in a few cases (notably Water and sewerage and Public administration).[34]

4.2 Monetary Policy Effects

In this section, we examine whether and how monetary policy shocks affect banking policies toward *greenwashers*. During 2022–23, the ECB tightened its monetary policy stance in response to the sharp increase in inflation. In particular, policy rates rose repeatedly and by more than markets had anticipated. These decisions were transmitted to the broader economy through various amplification mechanisms operating across multiple channels (Lane, 2023).

To assess the impact of monetary policy on our analysis, we construct a measure of monetary policy surprise MPS_t, defined as the forecast error between the actual main refinancing operations (MRO) interest rate announced at the ECB Governing Council meeting and its expectation as reported in the ECB Survey of Professional Forecasters.[35] In particular, we use the *nowcasted values*, that is, those submitted by forecasters in the same quarter as the official announcement. In practice, this amounts to studying contractionary surprises, since on average $MPS \geq 0$.[36]

We then analyze the role of monetary policy decisions by introducing this measure of unexpected surprise into Equation 8. The estimated results, where the dependent variables are the weighted average interest rate and the symmetric loan growth rate, are reported in Table 5 and Table 6.

$$\begin{aligned} s_{f,b,t} =& \beta_1 PD_{f,b,t} + \beta_4 GW_{f,t} + \beta_5 LR_{f,t} + \beta_6 COMP_{f,t} + \beta_7 GEAR_{f,t} + \beta_8 DUR_{f,b,t} \\ & + \beta_9 SHARE_{f,b,t} + \beta_{10} FT_{f,t} + \beta_{11} GB_{b,t} + \beta_{12} \left(GW_{f,t} \times GB_{b,t} \right) + \beta_{13} \left(FT_{f,t} \times GB_{b,t} \right) \\ & + \alpha_0 MPS_t + \alpha_1 \left(MPS_t \times PD_{f,b,t} \right) + \alpha_2 \left(MPS_t \times GW_{f,t} \right) + \alpha_3 \left(MPS_t \times FT_{f,t} \right) \\ & + \alpha_4 \left(MPS_t \times GB_{b,t} \right) + \alpha_5 \left(MPS_t \times GW_{f,t} \times GB_{b,t} \right) + \alpha_6 \left(MPS_t \times FT_{f,t} \times GB_{b,t} \right) \\ & + \theta_{f,b,t} + \varepsilon_{f,b,t} \end{aligned} \tag{8}$$

With Equation 8, we want to study how unexpected monetary policy tightening shapes banks' lending decisions by augmenting our baseline specification with the monetary policy surprise MPS and a set of interaction terms that allow the transmission of shocks to differ across

[34] As a robustness check, we also estimated the same model using the greenwashing proxy defined on the basis of end-2018 median emissions and reliability. Overall, the sectoral patterns remain qualitatively similar, suggesting that the heterogeneity is unlikely to be driven by contemporaneous changes in the GW classification.

[35] Grigioli et al. (2020) compute a similar metric in absolute terms, as their focus is on whether monetary surprises (regardless of sign) increase the dispersion of inflation forecasts. Altavilla et al. (2023), instead, define monetary policy surprises as changes in interest rates from 15 minutes before to 15 minutes after the official announcement, using the Euro Area Monetary Policy Event-Study Database (EA-MPD) created by Altavilla et al. (2019).

[36] Figure A.7 shows calculations based on both nowcasted (predictions in the same quarter; panel a) and forecasted values (predictions submitted in the previous quarter; panel b). For example, on 26 October 2023 the ECB announced an MRO rate of 4.5 percent. The following day, the ECB Survey of Professional Forecasters reported an average expectation for Q4 2023 of 4.43 percent, based on submissions between 29 September and 5 October. The resulting monetary surprise was therefore 0.07. Surprises based on forecasts from the previous quarter are generally larger.

Table 5: Bank lending, monetary policy and climate risk — Interest Rates

	Weighted average interest rate			
	[1]	[2]	[3]	[4]
PD	0.0016***	0.0185***	0.0027***	0.0026***
	(0.0005)	(0.0006)	(0.0006)	(0.0006)
GW	-0.0004***	-0.0009***	-0.0008***	-0.0010***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
LR			-0.0004***	-0.0003***
			(0.0000)	(0.0000)
COMP			-0.0042***	-0.0041***
			(0.0002)	(0.0002)
GEAR			0.0000***	0.0000***
			(0.0000)	(0.0000)
DUR			-0.0003***	-0.0003***
			(0.0000)	(0.0000)
SHARE			-0.0024***	-0.0041***
			(0.0002)	(0.0003)
FT			-0.0006***	-0.0005***
			(0.0001)	(0.0001)
GB			0.0012***	
			(0.0002)	
GW × GB			0.0007***	0.0009***
			(0.0002)	(0.0002)
FT × GB			-0.0000	-0.0006***
			(0.0002)	(0.0002)
MPS	0.0490***	0.0514***		
	(0.0006)	(0.0006)		
MPS × PD	0.0607***	0.0440***	-0.0094	-0.0052
	(0.0042)	(0.0043)	(0.0098)	(0.0089)
MPS × GW	0.0007	0.0033***	0.0092***	0.0102***
	(0.0006)	(0.0007)	(0.0014)	(0.0015)
MPS × FT			-0.0129***	-0.0114***
			(0.0020)	(0.0023)
MPS × GB			0.0112***	
			(0.0027)	
MPS × GW × GB			-0.0135**	-0.0113***
			(0.0022)	(0.0023)
MPS × FT × GB			-0.0077**	-0.0129***
			(0.0032)	(0.0034)
Time FE	No	No	Yes	No
Bank FE	Yes	Yes	Yes	No
Bank × Time FE	No	No	No	Yes
Firm FE	Yes	No	No	No
ILS FE	No	Yes	No	No
ILS × Time FE	No	No	Yes	Yes
Mat. FE	Yes	Yes	No	No
Mat. × Time FE	No	No	Yes	Yes
N	555,582	555,594	281,473	264,611

[1] *Note*: Standard errors are clustered at time-varying bank level.
[2] Standard errors in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

Table 6: Bank lending, monetary policy and climate risk — Outstanding Amounts

	Symmetric quarterly loans' growth rate			
	[5]	[6]	[7]	[8]
PD	-0.0587**	-0.0804***	-0.1001***	-0.1119***
	(0.0244)	(0.0194)	(0.0223)	(0.0222)
GW	-0.0014	-0.0042	-0.0112**	-0.0061
	(0.0033)	(0.0031)	(0.0051)	(0.0054)
LR			-0.0012	-0.0012
			(0.0016)	(0.0017)
COMP			-0.0394***	-0.0323**
			(0.0118)	(0.0125)
GEAR			-0.0000	-0.0000
			(0.0000)	(0.0000)
DUR			-0.0152***	-0.0170***
			(0.0013)	(0.0017)
SHARE			0.2047***	0.3729***
			(0.0098)	(0.0150)
FT			0.0350***	0.0281***
			(0.0064)	(0.0068)
GB			-0.0289**	
			(0.0147)	
GW × GB			0.0318**	0.0278**
			(0.0128)	(0.0131)
FT × GB			0.0178	0.0322**
			(0.0131)	(0.0137)
MPS	-0.0442***	-0.0307*		
	(0.0165)	(0.0168)		
MPS × PD	-0.0306	-0.1942*	0.1208	0.1866
	(0.1102)	(0.1009)	(0.2552)	(0.2745)
MPS × GW	0.0025	0.0079	0.1645***	0.1679***
	(0.0302)	(0.0304)	(0.0542)	(0.0599)
MPS × FT			-0.2893***	-0.2291**
			(0.0801)	(0.0962)
MPS × GB			0.1281	
			(0.1115)	
MPS × GW × GB			-0.3370***	-0.3071***
			(0.1119)	(0.1140)
MPS × FT × GB			0.0113	-0.1393
			(0.1271)	(0.1576)
Time FE	No	No	Yes	No
Bank FE	Yes	Yes	Yes	No
Bank × Time FE	No	No	No	Yes
Firm FE	Yes	No	No	No
ILS FE	No	Yes	No	No
ILS × Time FE	No	No	Yes	Yes
Mat. FE	Yes	Yes	No	No
Mat. × Time FE	No	No	Yes	Yes
N	281,473	500,871	254,514	238,635

[1] *Note*: Standard errors are clustered at time-varying bank level.
[2] Standard errors in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

borrower and bank types. Since MPS varies only over time, α_0 captures the average effect of a surprise on credit conditions, while α_1 tests the risk-taking channel by assessing whether shocks disproportionately affect riskier borrowers through $MPS \times PD$. We then examine whether monetary shocks alter the relative treatment of firms with sustainability-related attributes: α_2 and α_3 measure whether the pricing (and quantity) differentials associated with *greenwashing* (GW) and with the presence of a GHG emissions reduction target (FT) vary systematically with MPS. Crucially, the triple interactions $MPS \times GW \times GB$ and $MPS \times FT \times GB$ (coefficients α_5 and α_6) allow these effects to depend on bank type, that is, they test whether the shock-induced change in the GW (respectively, FT) discount differs between green and non-green banks.

In Table 5, we begin by assessing the role of monetary policy surprises *per se* by excluding time fixed effects. Column 1 includes MPS together with non-time-varying bank, residual maturity, and firm fixed effects, while column 2 replaces firm fixed effects with ILS FEs. Coefficients β_1 and β_4 remain statistically significant and preserve the same signs as in Equation 6. Moreover, in both columns the coefficient on the monetary surprise (α_0) is positive and highly significant, implying higher interest rates. Consistent with Altavilla et al. (2023), contractionary monetary surprises tighten loan pricing for riskier borrowers: α_1 is positive and statistically significant, in line with the risk-taking channel of monetary policy.[37]

Importantly, *greenwashers* hit by a negative monetary shock face a statistically significant deterioration in price conditions (coefficient α_2), which more than offsets the benefits obtained in the absence of monetary surprises (coefficient β_4). This suggests that monetary tightening strengthens banks' selection of borrowers during downturns. The result is robust to the inclusion of firm and relationship-specific controls (columns 3 and 4), which represent our preferred specifications.[38]

Overall, monetary policy tightening leads to a generalized increase in interest rates. This may influence banks' strategies in two opposite directions. On the one hand, intermediaries could prefer holding liquid assets rather than illiquid ones, thereby reducing credit supply as predicted by the bank-lending channel (Bernanke and Blinder, 1988; Bernanke and Gertler, 1995). On the other hand, after a prolonged period of low interest rates that compressed margins, a sharp increase in policy rates (such as in the recent tightening cycle) may stimulate a renewed search for profits, boosting lending activity (Borio and Gambacorta, 2017).

Table 6 presents estimations where the dependent variable is the symmetric loan growth rate. Baseline regressions (not interacted with monetary policy) yield results consistent with Table 2, while the coefficient on *greenwashing* (β_4) does not show robust statistical significance, indicating no clear evidence that euro area banks lend less to *greenwashers*. In columns 5 and 6, without time effects, the coefficient on the surprise (α_0) is negative and statistically significant, implying a contraction in credit supply. Finally, when controlling for firm and relationship characteristics (columns 7 and 8), the interaction between monetary surprises and the structured *greenwashing* proxy reveals significant positive effects (coefficient α_2), primarily driven by lending extended by non-green banks (see also coefficient α_5).

4.3 Testing the text-based *greenwashing* metric

In this section, we address our research question, that is, whether *greenwashing* enables companies to obtain more favorable access to bank credit, using the text-based metric presented in subsubsection 3.3.2.

[37] See Adrian and Shin (2010) and Jiménez et al. (2014) for a description of the risk-taking channel.

[38] Note that the combined effect $\alpha_2 + \alpha_5$ is also moderately significant ($p < 0.1$), indicating that the overall impact for greenwashers under a negative monetary shock remains statistically different from zero.

The analysis is restricted to Italian firms for which we simultaneously observe carbon emissions and the *trust* indicator from ISS-ESG, credit data from AnaCredit, and textual information from newspaper articles and corporate websites. The final sample comprises 86 firms. Although smaller than the structured dataset used in subsection 4.1, it remains sufficiently large (47,374 total observations) to yield statistically significant coefficient estimates.

We consider the following panel model regression

$$s_{f,b,t} = \beta_1 \, PD_{f,b,t} + \beta_4 \, GW_{f,t} + \boldsymbol{\beta}^\top Z_{f,t} + \theta_{f,b,t} + \varepsilon_{f,b,t}, \tag{9}$$

where Z collects the firm-level variables and bank–firm relationship controls other than PD and GW introduced in Equation 6.

For each *greenwashing* proxy, Table 7 reports two specifications that differ in the fixed effects included. In the odd-numbered columns, alongside ILS-by-time and maturity-by-time fixed effects, we add bank and time fixed effects separately; in the even-numbered columns, instead, we include bank-by-time fixed effects, which absorb bank specific shocks varying over time. As can be seen, the different fixed effects specifications do not lead to significant differences in the estimates.

As for GW, we consider two definitions. The first one, reported in the first two columns of Table 7 as ISS, is based on ISS-ESG carbon intensity emissions and reported trust. The second, indicated as ISS&TXT, classifies as greenwashers only those companies that report low carbon emissions and exhibit low reliability according to *both* ISS data and our trust metric TR_{txt} defined in Equation 3.

For interest rates, the first result to note is that the coefficient β_1, associated with the probability of default, is always positive and statistically significant, consistent with the regressions presented above. Turning to β_4, we find a consistently negative and statistically significant coefficient, indicating that banks tend to grant credit on more favorable terms to firms that *present* themselves as having stronger environmental performance, even when such claims lack credibility. This effect is particularly pronounced with the combined ISS&TXT proxy: the estimated coefficient is even larger, corresponding to a discount of about 70 basis points in credit access for firms classified as *greenwashers*. This underscores the usefulness of integrating our textual analysis with ISS data to improve the identification of potential greenwashers. By contrast, for the ISS-only proxy reported in the first two columns, one might expect the different sample composition to affect the sign or significance of the estimate relative to the previous sections, but this is not the case—the result remains robustly negative and significant.

As for loan volumes, no significant estimates are found: hence, there is no evidence that *greenwashing* practices may have either favorable or unfavorable effects.

5 Conclusions

The interplay between financial and environmental strategies has become increasingly evident. In particular, the lending policies adopted by credit institutions toward environmentally oriented sectors play a pivotal role in shaping sustainable development. Yet, deceptive practices such as greenwashing, where firms present their activities as environmentally sustainable while concealing their actual negative impact, threaten to undermine the effectiveness of these mechanisms.

This paper makes a first contribution by developing a novel measure of greenwashing behavior that combines both structured and unstructured data sources on firms and climate-related information. Specifically, we exploit structured climate data to construct a variable that captures the consistency and accuracy of reported environmental disclosures, alongside the carbon intensities disclosed by non-financial firms. We then complement this with a second proxy derived from

Table 7: Bank lending and text-based *greenwashing* metrics: Italian sample

	Weighted average interest rate			
	ISS	ISS	ISS&TXT	ISS&TXT
PD	0.0218***	0.0226***	0.0221***	0.0239***
	(0.0053)	(0.0051)	(0.0052)	(0.0051)
GW	-0.0018***	-0.0032***	-0.0069**	-0.0077**
	(0.0005)	(0.0007)	(0.0015)	(0.0028)
Firms' controls	Y	Y	Y	Y
Time FE	Yes	No	Yes	No
Bank FE	Yes	No	Yes	No
Bank x Time FE	No	Yes	No	Yes
ILS x Time FE	Yes	Yes	Yes	Yes
Mat. x Time FE	Yes	Yes	Yes	Yes
N	19,512	16,066	19,512	16,066

	Symmetric quarterly loans' growth rate			
	ISS	ISS	ISS&TXT	ISS&TXT
PD	0.4150	0.4110	0.4114	0.4101
	(0.2659)	(0.2842)	(0.2646)	(0.2835)
GW	0.0283	0.0352	-0.0533	-0.0641
	(0.0240)	(0.0282)	(0.1053)	(0.1115)
Firms' controls	Y	Y	Y	Y
Time FE	Yes	No	Yes	No
Bank FE	Yes	No	Yes	No
Bank x Time FE	No	Yes	No	Yes
ILS x Time FE	Yes	Yes	Yes	Yes
Mat. x Time FE	Yes	Yes	Yes	Yes
N	17,761	14,679	17,761	14,679

[1] *Note*: Standard errors are clustered at time-varying bank level.
[2] Standard errors in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < 0.01$.

textual analysis of corporate communication: information from newspapers and company websites. Our findings show that sentiment scores based on corporate websites are systematically higher than those from independent newspapers, suggesting that firms strategically use their own communication channels to overstate their sustainable profile. By combining these two metrics with firms' reported carbon emission levels, we construct a composite proxy capable of isolating companies that adopt suspicious communication strategies. This multi-sourced approach not only enhances the reliability of greenwashing detection but also provides a robust framework for assessing the gap between firms' environmental narratives and their real impact.

A second important result is that credit conditions in the euro area are systematically influenced by firms' carbon profiles and disclosure credibility, with evidence that greenwashing behavior affects the pricing of loans. Using granular ISS-ESG data for the euro area banking system over the period 2019–2023, we find that firms with higher carbon emissions generally faced higher interest rates, a kind of *pollution penalty*. However, the interest rate differential was significantly reduced when firms demonstrated greater credibility in the disclosure of their emissions data, even if they remained highly polluting. Our greenwashing proxy, defined using the ISS-ESG database as the combination of low reliability in disclosed information and low reported emissions, reveals that such *greenwashers* often managed to borrow at lower rates than their peers. At the same time, banks appeared to limit the overall volume of credit extended to these firms. Moreover, to test the robustness of these findings, we incorporate an unexpected monetary policy shock into the analysis. Strikingly, the interest rate discounts granted to greenwashers vanish when negative monetary surprises occur, suggesting that in periods of stress banks may improve their screening processes and tend to adopt stricter criteria in credit allocation.

Finally, when we combine the text-based reliability metric (capturing discrepancies between how firms present themselves on their websites and how they are portrayed in newspaper coverage) with the previous *greenwashing* proxy for Italian firms, we find broadly consistent results. This exercise highlights the added value of textual information in detecting potential misalignments between corporate self-representation and external assessments that may point to suspicious communication strategies. More generally, the inclusion of textual analysis strengthens our ability to identify cases where firms' sustainability narratives diverge from independent reporting, offering a complementary tool when traditional data sources are incomplete, costly, or difficult to access. Future research could build on this approach by expanding the green dictionary, adopting an embedding technique, incorporating additional climate-related datasets, extending the textual analysis to a broader euro area sample, and taking into account possible biases that may arise when firms and newspapers belong to the same holding group.

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A Appendix

Figure A.1: Computation of sentiment scores from companies' websites

id_iss	id_factiva	company	website	text	length	lemmatized	token	sentiment	sent_perc
YYYYY	xyzjw	XXXX SpA	http://www.XXXX.it	XXXX e struttura societaria Gestione del business Presenza geografica Mission e valori Etica del business e anticorruzione Gestione qualità, sicurezza e ambiente Sicurezza e c...	43500	[rete, gas, storia, strutturare, societario, gestione, business, presenza, geografico, mission, valore, etica, business, anticorruzione, gestione, qualità, sicurezza, ambiente, sicurezza, continui...	4050	68.0	0.156322

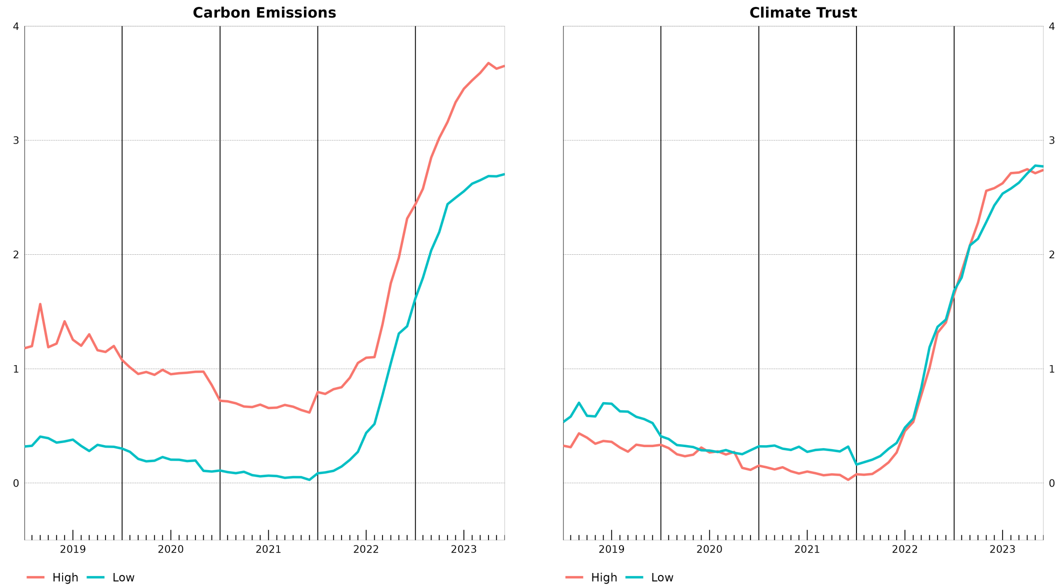
Source: Authors' calculations based on information from companies' websites. Text refers to the raw text extracted from the webpages, while lemmatized denotes the output after the lemmatization process. Sent_perc is the Average Sentiment Indicator (expressed as a percentage) derived from the web, as described in Equation 2. Length indicates the number of characters in Text, and Token represents the number of words in lemmatized.

Figure A.2: Computation of sentiment scores from companies' newspaper articles

id_iss	id_factiva	company	topic	text	length	lemmatized	token	sentiment	sent_perc
YYYY	xyz]w	XXXX SpA	Topic 1	A esprimere parere negativo nel corso delle due assemblee è stata la Regione rappresentata dall'assessore ai Trasporti AAAAAAA BBBB che ha chiesto al socio di maggioranza «di sospendere la delibe...	339	[esprimere, parere, negativo, correre, assemblea, regione, rappresentare, dallassessore, trasporti, antonio, moro, chiedere, socio, maggioranza, sospendere, deliberazione, aggiornare, riunione, lu...	27	0.0	0.000000
YYYY	xyz]w	XXXX SpA	Topic 2	Inizieranno il 29 maggio i primi lavori di asfaltatura che riguarderanno alcune strade comunali di ZZZZZZZ.\n\nI cantieri resteranno aperti fino al 23 giugno per interventi, dal costo complessi...	2157	[inizieranno, maggio, primo, lavoro, asfaltatura, riguardare, alcun, strada, comunale, belgioioso, cantiere, restare, aprire, giugno, intervento, costare, complessivo, 300mila, euro, puntare, ripr...	165	4.0	0.185443

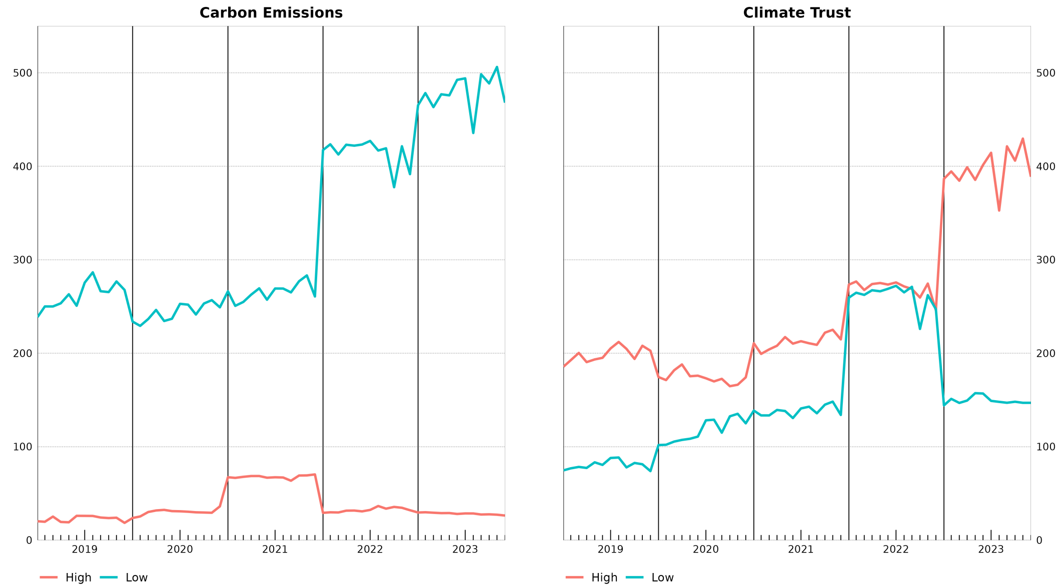
Source: Authors' calculations based on information from companies' newspaper articles. Text refers to the original text extracted from journal articles, while lemmatized denotes the output after the lemmatization process. The sent_perc values for articles concerning the same company are used to compute the Average Sentiment Indicator (expressed as a percentage) from the Factiva database, as described in Equation 1. Length indicates the number of characters in Text, and Token represents the number of words in lemmatized.

Figure A.3: Average interest rate by *greenwashing* drivers
(percentage values)



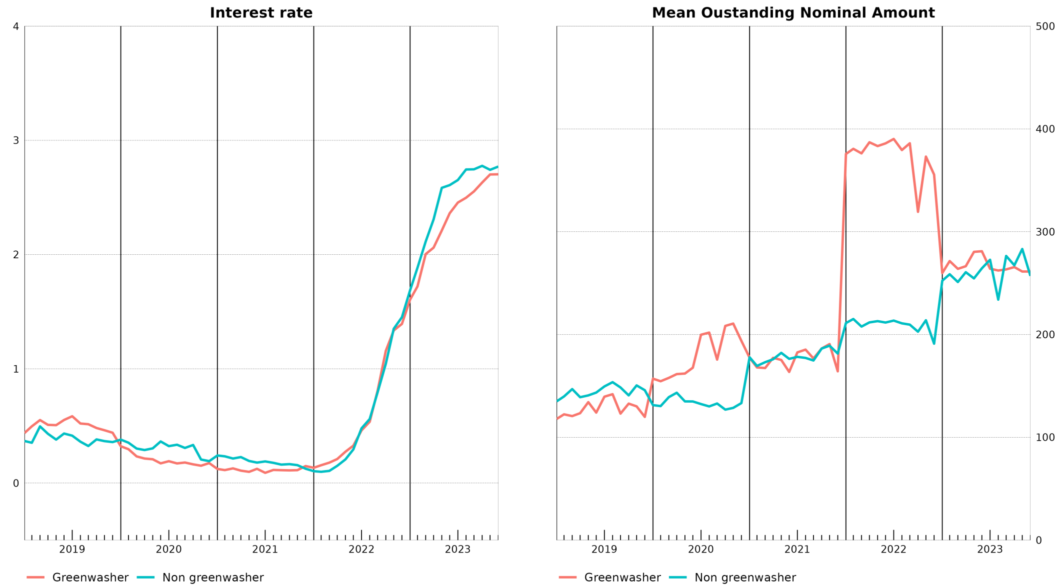
Source: authors' elaborations on ECB and ISS-ESG data.

Figure A.4: Mean outstanding amounts by *greenwashing* drivers
(millions of euro)



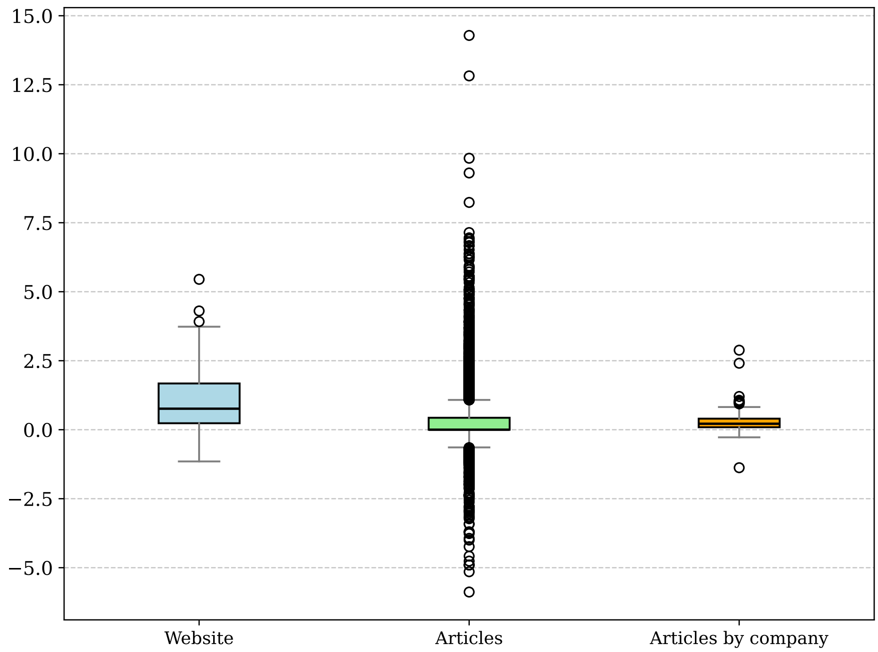
Source: authors' elaborations on ECB and ISS-ESG data.

Figure A.5: Average interest rate and mean outstanding amounts by *greenwashing* *(percentage values and millions of euro)*



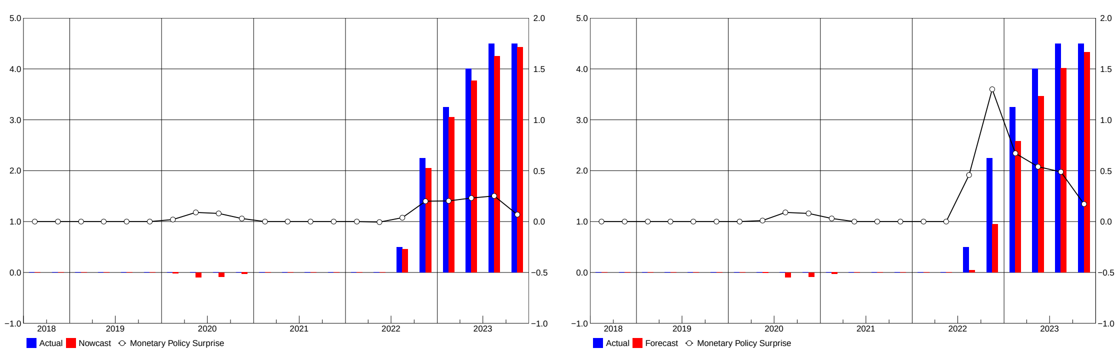
Source: authors' elaborations on ECB and ISS-ESG data.

Figure A.6: Comparison of the Sentiment Score Indicators



The boxplots illustrate the distribution of sentiment score indicators for company websites, newspaper articles, and articles grouped by company. Website scores have a higher median than articles and include a few high positive outliers, whereas articles show a median close to zero and a comparatively narrow interquartile range.

Figure A.7: Monetary Policy Surprise
(percentage values)



(a) Actual and nowcasted MROs' interest rates.

(b) Actual and forecasted MROs' interest rates.

Source: authors' elaborations on ECB data. The left axis refers to the actual and expected interest rate on the Main Refinancing Operations (MRO) whereas the right one is related to the Monetary Policy Surprise (MPS). MPS is computed as the difference between the announced and expected values of the interest rate on the ECB's MROs reported by the ECB Monetary Policy Decisions and ECB Survey of Professional Forecasters, respectively. In panel (a) expected interested rates are nowcasted in the same quarter of the official announcement whereas in panel (b) they are forecasted in the previous quarter with respect to the announcement.

Table A.1: Descriptive Statistics

	Observations	Mean	Std. Dev.	p25	p50	p75
Agreed interest rate	697,570	0.01	0.02	0.00	0.01	0.02
Log Amount	697,570	15.20	2.84	13.57	15.13	17.05
Probability of default	697,570	0.02	0.09	0.00	0.00	0.00
Carbon Intensity	753,836	0.12	0.67	0.00	0.01	0.03
Total Climate Trust	740,649	0.86	0.12	0.80	0.91	0.95
Reported Climate Trust	658,368	0.86	0.12	0.81	0.91	0.95
GHG Reduction Target	749,214	0.77	0.42	1.00	1.00	1.00
Green Bank	787,277	0.17	0.38	0.00	0.00	0.00
Liquidity Ratio	385,535	1.29	1.34	0.79	1.00	1.31
Composition	374,641	0.21	0.24	0.05	0.14	0.27
Gearing Rate	372,955	142.45	124.28	69.32	107.61	177.10
Number of employees (thousands)	495,745	62.31	94.63	8.71	26.75	82.97
Log Total Assets	523,954	24.42	2.79	22.84	24.47	26.35
Log Revenue Turnover	372,955	22.52	1.80	21.65	22.63	23.77
Duration (months)	754,099	5.73	3.48	3.00	5.00	9.00
Share (%)	780,984	12.00	24.00	0.00	1.00	9.70
Residual Maturity (months)	666,312	18.21	26.80	0.00	2.39	31.07
Monetary Policy Surprise	787,277	0.07	0.09	0.00	0.02	0.09

Source: authors' elaborations on ECB, Orbis and ISS-ESG data.

Table A.2: Summary statistics of newspaper articles

Metric	1st Qu.	Median	Mean	3rd Qu.	Max.
Article length (characters)	1,310	2,440	3,122	3,832	116,518
Number of articles per company	9.00	33.00	55.63	106.25	150.00
Text length per company (characters)	26,593	100,208	173,700	297,038	694,203
Total number of articles					10,348
Distinct companies identified					186

Source: authors' elaboration on Factiva data.

Table A.3: Identification of the Structured-based *Greenwashing*

	Reported Carbon Intensity	
Climate Trust in Reporting	Low	High
Limited	**Greenwashing**	Brownwashing
Elevated	Greentrusting	Browntrusting

Source: authors' definitions based on ISS-ESG data. Firms are classified as *greenwashers* when they report low emissions (below the median for each reporting date, sector, and country) while simultaneously showing low trust in reporting, that is limited credibility and consistency in their environmental disclosures.

Table A.4: Number of firms and loan descriptive statistics by year

Year	Number of unique firms	Average Interest Rate (*percentage values*)	Mean of Outstanding Amounts (*euro millions*)
2019	846	0.37	139.82
2020	842	0.20	145.89
2021	858	0.11	177.88
2022	912	0.57	260.65
2023	860	2.51	258.28

Source: authors' elaboration on AnaCredit data.

Table A.5: Greenwashers by Firms' Characteristics

	Time-Varying Greenwashing			Predetermined Greenwashing		
	No	Yes	Total	No	Yes	Total
			Economic Activity			
Manufacturing	157	88	245	123	120	243
Construction	9	3	12	5	7	12
Services	264	122	386	183	194	377
Other activities	156	67	213	92	126	218
			Total Assets			
≤ 43 m EUR	1	0	1	1	0	1
> 43 m EUR	585	270	855	402	447	849
			Turnover			
≤ 50 m EUR	7	4	11	5	5	10
> 50 m EUR	579	266	845	398	442	840
			Employees			
≤ 250	12	12	24	12	11	23
> 250	574	298	832	391	436	827
			Location			
Europe	335	125	460	239	218	457
Rest of the world	251	145	396	164	229	393
			GHG Reduction Target			
No	142	76	218	77	132	209
Yes	428	185	613	318	298	616
Missing	16	9	25	8	17	25
Total	586	270	856	403	447	850

Source: authors' elaborations on ECB, Orbis, and ISS-ESG data. Results refer to 2023. The *time-varying* criterion is assessed at each reference date by calculating medians for carbon intensity and climate trust across time, country, and economic activity. The *predetermined* criterion is based on the classification at the end of 2018, which is kept constant over the entire sample period and is used only as a robustness check.

Table A.6: Sample of the Green dictionary

Italian term	English term	Polarity
Adattamento climatico	Climate adaptation	1
Ambiente	Environment	1
Cambiamento climatico	Climate change	-1
Carbone	Coal	-1
Decarbonizzazione	Decarbonization	1
Economia verde	Green economy	1
Efficienza energetica	Energy efficiency	1
Emissioni	Emissions	-1
Energia fossile	Fossil energy	-1
Energia rinnovabile	Renewable energy	1
Energie pulite	Clean energy	1
Incentivi verdi	Green incentives	1
Innovazione verde	Green innovation	1
Investimenti sostenibili	Sustainable investments	1
Investimento ESG	ESG investment	1
Investimento fossile	Fossil investment	-1
Neutralitá carbonica	Carbon neutrality	1
Petrolio	Oil	-1
Riscaldamento globale	Global warming	-1
Solare	Solar	1
Sostenibilitá	Sustainability	1
Transizione energetica	Energy transition	1
Transizione verde	Green transition	1

Extract from the green dictionary defined by the authors. Italian and English terms are shown prior to stemming and lemmatization, with polarities of 1 and –1 assigned to positive and negative concepts, respectively.

Table A.7: Sample of Valence Shifters

Italian term	English term	Valence Shifter
un rallentamento	slowdown	-1
senza	without	-1
non	not	-1
indebolito	weakened	-1
chiaramente	clearly	2
molto	very	2
rilevante	relevant	2
specialmente	especially	2
sufficientemente	sufficient	0.5
quasi	almost	0.5
leggermente	slightly	0.5
improbabile	unlikely	0.5

Extract from the list of valence shifters defined by the authors. They include negators, amplifiers, and deamplifiers with polarities of -1, 2 and 0.5 respectively. All valence shifters in this table are shown prior to stemming and lemmatization.

Table A.8: Descriptive Statistics of Textual Dataset

	Observations	Mean	Std. Dev.	p25	p50	p75
Website Tokens	202	5,621.80	13,201.14	640.20	1,347.50	4,561.50
Article Tokens	10,348	281.30	289.95	119.00	224.00	350.00
Article Tokens by Firm	186	15,649.00	15,785.80	2,450.00	9,250.00	26,101.00
Website Sentiment	202	1.10	1.09	0.23	0.76	1.68
Article Sentiment	10,348	0.31	0.86	0.00	0.00	0.43
Article Sentiment by Firm	186	0.29	0.38	0.09	0.22	0.40
Δ^{sent}	181	-0.84	1.14	-1.55	-0.54	-0.02

Source: authors' elaboration based on data from company websites and newspaper articles.

Table A.9: Statistical Test for Differences in Mean Sentiment Scores

	Websites vs Articles	
	All companies	By Company
t-statistic	10.2430	9.9129
p-value	0.0000	0.0000

Null hypothesis (H_0): the difference in mean sentiment scores is equal to 0.

Source: authors' elaboration based on data from company websites and newspaper articles.