From unrated to rated: How ESG ratings impact the debt pricing of listed firms?

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Abstract

This paper investigates the causal effect of ESG rating initiation on corporate borrowing costs. Using a staggered difference-in-differences design, we analyze a panel of Italian publicly listed non-financial firms from 2013 to 2023. We find that becoming ESG-rated leads to a statistically and economically significant reduction in the firm's cost of debt. On average, the cost of debt declines by approximately 90 basis points following ESG rating initiation. This effect strengthens over time indicating that the benefits of ESG certification in debt markets accumulate as lenders incorporate the ESG information. These findings hold up under a range of robustness tests including various matching strategies, alternative difference-in-differences estimators, placebo tests, and the use of different control groups. Moreover, this relation is stronger for firms that are financially constrained, highly levered, and capital-intensive, as well as firms operating in low carbon industries. Overall, our results offer causal evidence that getting ESG-rated lead to lower cost of debt.

Keywords: Environmental, Social, and Governance (ESG) ratings; Cost of debt; Corporate borrowing costs; Sustainable finance

JEL Classification: G32, G14, M14

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1. Introduction

The growing interest on sustainable investing and stakeholder capitalism has brought Environmental, Social and Governance considerations within both corporate and financial decision-making. Bloomberg's 2024 report indicates that global ESG assets under management surpassed $30 trillion in 2022, with projections suggesting a potential increase to $40 trillion by 2030. This marks a significant move from niche activism to mainstream capital allocation.

Credit markets have traditionally relied on accounting- and market-based risk measures, such as credit ratings. More recently, however, credit markets have looked beyond traditional financial indicators and taken non-financial information into account when evaluating borrower risk and long-term solvency. ESG ratings, which summarize a firm's environmental, social, and governance performance, are now often used by creditors and credit rating agencies alongside conventional financial indicators to evaluate transparency and exposure to non-financial risks. Against this background, examining the effect of ESG ratings on financing costs is of clear practical and academic importance.

Despite the rapid growth of ESG-focused investing, empirical evidence on how ESG ratings affect corporate borrowing costs remains limited. Existing evidence is largely associational and does not establish clear causal effects. Firms that become ESG-rated may differ systematically from firms that remain unrated in ways that are difficult to observe, and improvements in ESG performance may be endogenous to other changes in firm quality. Consequently, identifying the causal effect of ESG rating initiation on borrowing costs is important. We fill this gap by treating first-time ESG rating initiation as an information shock to lenders and testing how cost of debt adjusts around the event.

We focus on ESG rating initiation rather than rating levels because ESG scores are vendor-specific and not directly comparable across agencies (Berg, Kölbel, and Rigobon, 2022; Avramov et al., 2022), whereas initiation is a discrete and well-defined shift in a firm's information environment. Since LSEG scores are constructed from public disclosures and coverage expansion follows broad provider criteria (e.g., size, index inclusion, disclosure availability), firms have limited ability to precisely time coverage, making initiation akin to an externally imposed change in information availability and comparability (see Section 3.3 for a more detailed discussion).

We ground our analysis in classic theories of information asymmetry in credit markets and the voluntary-disclosure literature, which predict that reducing information asymmetry between borrowers and lenders lowers the risk premia required to compensate for uncertainty about borrower quality (Myers and Majluf, 1984; Stiglitz and Weiss, 1981; Sengupta, 1998; Healy and Palepu, 2001; Francis et al., 2005). In standard adverse selection models of credit markets, when lenders cannot fully distinguish borrower quality, they either charge high interest spreads or ration credit, particularly among more opaque borrowers for whom private information problems are especially severe (Stiglitz and Weiss, 1981). Any mechanism that credibly improves transparency and signals firm quality can relax these frictions (Spence, 1973; Megginson and Weiss, 1991; Chemmanur and Fulghieri, 1994). The very first issuance of an ESG rating can be seen as an informational certification which converts previously qualitative, fragmented, or self-reported sustainability information into a standardized and externally validated score. An ESG rating can mitigate lenders' uncertainty and adverse selection issues by offering a reliable evaluation of a firm's ESG practices and risk management. In essence, obtaining an ESG rating is an information event that could allow banks and bond investors to better incorporate ESG-related risks into their pricing decisions (Delis et al., 2019; Capasso et al., 2022). This is in line with evidence from credit ratings literature which demonstrate that more informative ratings can influence credit spreads and financing costs without altering any underlying firm fundamentals (Tang, 2009; Kisgen and Strahan, 2010). We posit that a similar mechanism may operate for ESG rating, i.e., being ESG-rated could serve as a positive signal of firm quality and long-term prospect, thereby influencing the interest rates that lenders charge.

We use a difference-in-differences approach to test whether firms' cost of debt changes after they receive an ESG rating, compared with similar firms that do not receive a rating over the same period. Because firms become rated at different times, we do not rely on the standard two-way fixed effects model. We use the Callaway and Sant'Anna (2021) approach which is designed for staggered adoption and allows the effects to vary across firms and over time. We first use propensity score matching to pair treated firms with control firms that have not yet been rated to ensure that treated and control firms are comparable. We then estimate average treatment effects on the treated within this matched sample, using the multi-period DiD framework.

Our findings indicate that becoming ESG-rated leads to a substantial reduction in firms' borrowing costs. Baseline estimates indicate that the initiation of an ESG rating is associated with an average decline of around 90 basis points in firms' cost of debt. This effect is statistically and economically significant and represents a 20% reduction in cost of deb to the sample's mean which translate into considerable interest savings for firms. A reduction of such magnitude can translate into considerable interest savings for firms. This is consistent with credit markets placing material value on standardized ESG information. Moreover, the effect appears to strengthen over time. We find that the drop in interest rates is smaller in the immediate aftermath of rating initiation and grows larger in subsequent years. This temporal pattern suggests that lenders may initially take note of the new ESG information and gradually incorporate it more fully into lending terms as the firm's rated status becomes entrenched and perhaps as the firm continues to maintain or improve its ESG performance. Importantly, we observe no significant changes in the cost of debt for treated firms before they receive an ESG rating which supports the parallel trends assumption and a causal interpretation of the results.

We subject our results to a battery of robustness checks. First, we verify that the findings are not sensitive to how the control group is constructed or how the DiD model is estimated. The baseline uses one-to-one nearest-neighbour matching without replacement. As a robustness test, we match each treated firm to multiple controls (i.e., 1 to 3 and 1 to 5 matching) and re-estimate our main model. We also obtain very similar treatment effect estimates using alternative estimators within the Callaway–Sant'Anna framework (i.e., inverse-probability weighting only, or outcome regression only), as well as using event-study estimators proposed by Sun and Abraham (2021). In all cases, the findings remain qualitatively similar that firms experience a sizable decline in borrowing costs after becoming ESG-rated. We also conduct placebo tests to ensure that our results are not driven by spurious time trends or unobserved shocks. We randomly assign "fake" ESG rating initiation years to firms that never actually received a rating during our sample period, then re-estimate the model. These random assignments produce no systematic reduction in cost of debt, and the distribution of placebo effects is centered near zero, far from our actual estimated effect. We also experiment with alternative control groups. We use only firms that never obtain an ESG rating as the comparison group. Our main result persists, which suggests that the choice of control group or sample composition is not driving the outcome. Taken together, these robustness tests indicate that the decline in the cost of debt following ESG rating initiation is not an artifact of a particular specification, estimator, or control-group construction.

In addition to the average effect, we also investigate how the relation between ESG ratings initiation and cost of debt varies across firm characteristics. We find that the reduction in the cost of debt is most pronounced in firms in which financial frictions are more prominent. Particularly, financially constrained firms (indicated by having high SA index) experience greater and earlier reductions in cost of debt, consistent with the notion that ESG ratings serve as an external certification that reduces information asymmetry and alleviates creditor concerns. We also find that the relation between ESG initiation and cost of debt is stronger for highly leveraged firms, indicating that lenders are especially more sensitive to credible signals of risk management and governance quality in highly levered firms. The relation is more pronounced for capital-intensive (high tangibility) firms because ESG risks are more material and more tied to observable assets and capex, making ratings more verifiable and easier for banks to incorporate into credit screening, monitoring, and internal risk frameworks. Finally, firms in greener (low-carbon) industries show larger cost of debt reductions than those in brown industries, plausibly because lenders view them as lower transition-risk borrowers and because green exposures help banks meet portfolio decarbonization goals and respond to supervisory and investor pressures. Overall, the heterogeneity results indicate that ESG ratings deliver the greatest borrowing-cost benefits when they meaningfully improve creditors' ability to assess and price risk.

Our study contributes to three main strands of literature. First, it adds to literature on the determinants of corporate borrowing costs by demonstrating that non-financial information, particularly ESG rating initiation, can materially affect debt pricing, hence complimenting existing evidence on certification and credit-risk pricing in debt markets. Second, our study advances the literature on ESG pricing by showing that ESG information is priced not only in equity markets but also by creditors, thereby linking ESG disclosure to the terms of loan and bond financing. Third, our finding contributes to the broader literature on disclosure, transparency, and information economics by showing how greater disclosure (i.e., third-party ESG ratings) can alleviate information asymmetry and yield economically meaningful financing benefits. Our findings also have practical implications. For firms, especially those facing tighter financing conditions, obtaining credible ESG coverage can be associated with meaningful interest-cost savings. For lenders and investors, the results indicate that ESG information is priced in credit markets, and that ESG ratings can be a useful input for screening and risk-based pricing. For policymakers and standard setters, the evidence is consistent with the view that improving the availability and standardization of ESG information can have real financing consequences.

The remainder of the paper is structured as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 describes the data sources, sample construction, and the empirical methodology. Section 4 presents the main results. Section 5 discusses various robustness tests. Section 6 provides the result for heterogeneity of effects across firms and Section 7 concludes the paper.

2. Literature Review and Hypothesis Development

2.1. ESG ratings and Cost of Debt

The relationship between information, perceived risk, and the cost of debt has long been central to corporate finance and financial intermediation. In classical capital structure theory, the cost of debt plays an important role in determining firms' optimal leverage and financing mix. The trade-off model suggests that lower expected default and monitoring costs expand a firm's debt capacity (Kraus & Litzenberger, 1973). the pecking-order theory argues that information asymmetry pushes firms toward internal funds and financing options that are less sensitive to such frictions (Myers & Majluf, 1984). A broad range of studies converge on the idea that when credible, verifiable, and standardized information about a firm becomes available to lenders, informational frictions decline and credit pricing adjusts accordingly. Within this framework, the first-time assignment of an ESG rating can be viewed as an informational activation event: it transforms previously qualitative, fragmented, or self-reported signals about firms' environmental, social, and governance practices into codified and externally validated information that can be embedded in risk assessments, internal models, and lending decisions.

The conceptual foundations lie first in the theory of information asymmetry. In their seminal contribution, Stiglitz and Weiss (1981) show that when lenders cannot perfectly distinguish among borrowers of different quality, credit markets do not clear through price alone. Higher interest rates exacerbate adverse selection and moral hazard, so lenders respond by rationing credit or embedding a premium for opacity in loan contracts. In such a setting, any mechanism that enhances the credibility, comparability, and verifiability of information on borrower quality can reduce the required risk premium. Subsequent work on disclosure confirms that higher-quality and more transparent reporting is associated with lower required returns, as improved information reduces estimation risk and uncertainty about future cash flows (Healy & Palepu, 2001; Sengupta, 1998; Francis et al., 2005). From this perspective, an ESG rating functions as a structured disclosure device that converts aspects of firms' risk profiles—previously classified as "soft" or non-financial—into "hard" information. By mitigating opacity on ESG-related risks and policies, the rating enriches the information set used by lenders and, in principle, can decrease the cost of debt.

This logic is supported by signalling and certification theories. When there is asymmetric information, high-quality agents can set themselves apart from low-quality ones by undertaking observable and costly actions that credibly convey their type. In corporate finance, third-party certification, i.e., through reputable underwriters, auditors, venture capitalists, or rating agencies, operates as such a signal, increasing the credibility of firm-specific information and reducing perceived risk (Megginson & Weiss, 1991; Chemmanur & Fulghieri, 1994). The credit ratings literature offers a clear illustration of how the informational content and institutional standing of external assessments shape financing conditions. Tang (2009) shows that the refinement of Moody's rating scale, which increased rating precision without altering underlying fundamentals, led to lower bond spreads, underscoring the value of more informative ratings. Kisgen and Strahan (2010) further show that once ratings enter regulatory constraints, they affect firms' decisions and associated costs. These insights underline a general mechanism: when external assessments become more precise, standardized, and institutionally embedded, markets incorporate them into the pricing of credit risk. ESG ratings represent an extension of this certification logic into the non-financial domain. By subjecting firms to a formalized and externally validated ESG evaluation, they generate signals about risk management quality, transparency, and commitment that can be readily processed by lenders and may justify tighter spreads.

A complementary rationale is provided by the theory of delegated monitoring and the economics of relationship banking. Diamond (1984) formalizes the role of financial intermediaries as delegated monitors: banks exist because they can acquire and verify information about borrowers more efficiently than dispersed investors. The effectiveness and cost of this monitoring depend critically of monitoring depend heavily on the structure and verifiability of available information. Boot (2000) and Berger and Udell (1998) shows that banks, particularly in SME lending, rely on a combination of hard information (quantitative and standardized) and soft information (qualitative and relationship-specific), with soft information being costly to gather and difficult to transmit across organizational layers. The introduction of ESG ratings changes this informational landscape by converting some soft dimensions such as environmental compliance, stakeholder relations, and governance practices, into standardized indicators. These indicators can enter internal rating systems, screening practices, and covenant structures, thereby reducing monitoring costs, increasing comparability across borrowers, and improving the reliability of long-term assessments. Theoretical models of delegated monitoring imply that such efficiency gains in information production and verification can be shared with borrowers through more favorable contractual terms, including lower loan spreads and more accommodative credit conditions.

Regulatory and supervisory changes further increase the economic importance of standardized ESG information. Recent guidance from the European Central Bank (ECB, 2022) and the European Banking Authority (EBA, 2023) requires banks to systematically identify, assess, and manage ESG risks across their governance frameworks, credit processes, and risk management systems. As a result, these requirements generate institutional demand for ESG ratings at the counterparty level that are consistent and useful for decision-making. ESG ratings can meet this demand by offering structured measures that can be mapped into internal models, portfolio concentration limits, and climate or environmental risk assessments. At the same time, loans and securities associated with firms that are credibly assessed on ESG dimensions can be more easily included in green or sustainability-linked funding instruments, potentially reducing banks' own cost of funding. Recent evidence confirms that banks integrating ESG factors into their risk models adjust loan pricing, accordingly, favoring borrowers with stronger ESG practices (Delis et al., 2019; Capasso et al., 2022). In such an environment, credible ESG information acquires incremental economic value for intermediaries: it facilitates regulatory compliance, supports strategic balance-sheet management, and increases the scope for aligning assets with ESG-sensitive investors. When these benefits materialize, part of the gain can be passed through to borrowers via adjusted pricing and conditions, creating an additional channel through which ESG-related information affects the cost of debt.

More recently, Asimakopoulos et al. (2023) provide more direct evidence on these informational channels by studying the consequences of obtaining an ESG rating. They show that the first-time provision of an ESG rating reduces information asymmetry and reshapes firms' debt structure, as rated firms substitute bond financing with bank loans and adjust their target leverage ratios downward. Their results are consistent with both signaling and pecking-order arguments, supporting the view that ESG ratings act as credible signals that modify lenders' and investors' perceptions of firm quality. However, while they document significant effects on debt composition and leverage, the implications for the cost of debt remain largely unexplored—an issue that the present study directly addresses.

These theoretical arguments find growing empirical support in recent corporate-finance research, which investigates how firms' sustainability attributes and ESG-related information affect financing costs, capital access, and debt composition. A first group of studies shows that stronger environmental and social performance, or more credible sustainability disclosure, is associated with a lower cost of capital, in line with reduced information risk and perceived default risk: firms with better environmental risk management or CSR performance enjoy cheaper financing or relaxed financing constraints, while weaker ESG profiles face tighter conditions (Sharfman & Fernando, 2008; El Ghoul et al., 2011; Cheng et al., 2014; Ng & Rezaee, 2015). A complementary set of contributions emphasizes that lenders and bond investors penalize specific ESG concerns: banks and debt markets charge higher spreads to borrowers with pronounced environmental or social controversies and reward the absence of such concerns, indicating that non-financial risk is explicitly incorporated into credit pricing (Goss & Roberts, 2011; Chava, 2014; Oikonomou et al., 2014).

Relational and reputational factors also matter. Firms with higher social capital and stronger stakeholder trust get lower loan spreads, better covenants terms and broader funding access whereas these benefits are particularly pronounced during periods of unceratinities, showing indicating credible signals of reliability carry real credit value (Hasan et al., 2017; Lins et al., 2017). Evidence on instrument-level innovations such as certified green bonds further shows that when ESG attributes are independently verified and standardized, they attract dedicated investor demand and contribute to distinct pricing dynamics (Flammer, 2021). Finally, research on climate and environmental risks shows that measurable exposures to such risks are reflected in higher loan spreads and bond yields, confirming that ESG risk indicators have become standard inputs in lenders' credit assessments (Javadi & Masum, 2021). Taken together, these findings confirm that markets and intermediaries respond to reliable ESG information, both positive and negative, through adjustments in the cost and conditions of debt, in a manner fully consistent with the informational, signalling, and monitoring channels outlined above.

Across these strands of research, a coherent picture emerges. Information-asymmetry models highlight that opacity commands a premium in loan pricing; signaling and certification theories explain how credible third-party assessments transform unobservable attributes into trusted signals; delegated-monitoring frameworks show that standardized and verifiable information reduces the cost of financial intermediation; and regulatory developments increase the institutional value of robust ESG metrics. Within this integrated framework, the first-time assignment of an ESG rating can be understood as a specific informational event that activates these established mechanisms: by codifying non-financial information into an auditable standard, it reduces uncertainty and monitoring costs and provides a theoretically grounded channel through which the cost of debt may adjust. The growing regulatory and market emphasis on ESG integration further amplifies the relevance of this mechanism, making the understanding of how ESG rating assignments affect debt pricing both timely and policy relevant.

2.2. Hypothesis development

Building on the theoretical arguments and empirical evidence discussed above, we formally develop our testable hypotheses. Our predictions stem from four interrelated channels including information asymmetry reduction, signalling and certification, delegated monitoring, and the growing institutional integration of ESG risk into credit assessment. Each hypothesis maps a specific channel (or an interaction between channels and firm characteristics) into a directional prediction about the cost of debt.

2.2.1. ESG Rating Initiation and the Cost of Debt

When borrower quality is not fully observable, lenders reflect the resulting uncertainty in the pricing of loans (Stiglitz and Weiss, 1981). When information is incomplete or difficult to verify, lenders either charge higher interest rates or restrict credit supply. The first-time assignment of an

ESG rating converts qualitative and self-reported ESG information into a standardized, externally verified measure. This helps in the reduction of uncertainty surrounding future cash flows, regulatory risk and the corporate governance quality. As a result, lenders can more accurately evaluate borrower risk and may therefore demand a smaller opacity premium.

Signaling and certification theories leads to similar implications. External ESG assessments can function much like credit ratings and other credible third-party certifiers. That is, they convert unverifiable firm characteristics into signals that lenders can use in their pricing models (Megginson and Weiss, 1991; Chemmanur and Fulghieri, 1994; Tang, 2009). If lenders interpret ESG rating initiation as a positive signal of risk management quality and long-term resilience, borrowing costs should decline.

The delegated monitoring theory further supports this predictor. It states that standardized ESG metrics reduce banks' monitoring and screening costs. ESG ratings partially convert soft information into hard, verifiable indicators that can be embedded into internal risk models, covenant design, and portfolio management systems. Lower monitoring costs and better risk assessment can convert into tighter spreads.

Finally, the increasing regulatory and supervisory emphasis on ESG risk integration strengthens the economic value of such standardized information. When banks face institutional pressure to measure and manage ESG risks systematically, firms that become ESG-rated provide more decision-useful inputs for credit allocation. This creates an additional channel through which ESG rating initiation may affect debt pricing. Taken together, these mechanisms converge on a common prediction: ESG rating initiation should reduce firms' borrowing costs.

Hypothesis 1 (H1): *The initiation of an ESG rating is associated with a reduction in a firm's cost of debt.*

2.2.2. Dynamic Effects of ESG Rating Initiation

The theoretical framework also implies that the effect of ESG rating initiation may not be instantaneous. Although lenders observe the rating in the year of assignment, full incorporation into pricing decisions may occur gradually for several reasons. First, internal credit models covenant templates, and risk-management systems gradually incorporate new ESG metrics. Second, lenders attach greater weight to the rating once rating status has persisted and ESG performance has proven stable, before adjusting spreads more aggressively. Third, the informational content of the rating improves with the firm's ESG track record. This argument is consistent with learning models in financial markets, where new information is incorporated progressively as its credibility and persistence are validated. Consequently, the reduction in the cost of debt may become more pronounced over time.

Hypothesis 2 (H2): *The reduction in the cost of debt following ESG rating initiation increases over time.*

2.2.3. Cross-Sectional Heterogeneity

The theoretical channels outlined above imply that the impact of ESG rating initiation should be stronger in settings where informational frictions are more pronounced or where ESG risks materiality are greater, such us for more financially constrained and leveraged firms operating in capital-intensive and high-carbon sectors.

Financially Constraints

Firms facing tighter financial constraints suffer more acutely from information asymmetry and a higher opacity premium in credit pricing (Kaplan and Zingales, 1997; Hadlock and Pierce, 2010). In this setting, external certification can particularly be valuable because it helps alleviate creditor uncertainty and may expand firm's financing opportunities. The marginal informational value of an ESG rating is therefore larger for these firms.

Hypothesis 3a (H3a): *The negative effect of ESG rating initiation on the cost of debt is stronger for financially constrained firms.*

Leverage

Firms that are highly leveraged operate closer to their debt capacity, and lenders bear a larger share of downside risk when lending to such firms. Therefore, incremental information about governance quality and risk management is weighed more heavily in credit pricing. This implies that ESG rating initiation for highly levered firms should produce larger reductions in spreads.

Hypothesis 3b (H3b): *The reduction in the cost of debt following ESG rating initiation is stronger for highly leveraged firms.*

Capital Intensity

Capital-intensive firms are particularly exposed to environmental regulation, transition-driven asset obsolescence and long horizon investment decisions whose value depends on ESG risks. These risks can materially affect both collateral values and the durability of future cash flows but difficult for lenders to infer from financial statements alone. Standardized ESG ratings can reduce this long-horizon opacity, so the pricing effect should be stronger for capital-intensive firms.

Hypothesis 3c (H3c): *The reduction in the cost of debt following ESG rating initiation is stronger for capital-intensive firms.*

Industry Environmental Exposure

The direction of the effect is, ex ante, ambiguous. On the one hand, the information-asymmetry view suggests a larger effect in high-carbon industries where ESG risks are more material and an ESG rating may reduce greater uncertainty. Whereas, on the other hand, the sustainable-finance demand channel suggests a stronger effect in greener industries, where a rating may reinforce an already favorable environmental profile and improved access to ESG-oriented funding. Given the growing importance of EU sustainable-finance regulation during our sample period, which increased the salience of ESG-based capital allocation and eligibility considerations, we expect the latter channel to be more relevant.

Hypothesis 3d (H3d): *The reduction in the cost of debt following ESG rating initiation is stronger for firms operating in greener industries.*

3. Data

3.1. Database and Sample

Our sample consists of all Italian non-financial firms listed on Borsa Italiana for which we have complete data on financials and ESG ratings in the period from 2013 to 2023. Financial data are obtained from the AIDA database (by Bureau van Dijk) which provides detailed firm-level accounting information for Italian companies. We use consolidated financial statements. We focus on non-financial firms and exclude banks, insurance firms, and other financial institutions (NACE codes between 6400 and 6699) because financial firms have different capital structure norms and are subject to regulatory capital requirements. We merge the firm fundamentals with ESG rating data from the London Stock Exchange Group (LSEG) (formerly Refinitiv). The LSEG ESG data provides a combined ESG score and the score at pillar level (Environmental, Social, Governance, etc.) for firms that are covered. We also winsorize continuous variables at 1st and 99th percentiles to limit the influence of outliers.

3.2. Sample construction

We start with 520 listed firms (5,200 firm-years) from AIDA for the ten years between 2013 and 2023. As summarized in Appendix A.1, we first remove 44 firms (440 firm-years) which were delisted before 2014 to keep all entrants within the observation window and avoid left-censoring of treatment timing. We then exclude 59 financial institutions (NACE codes between 6400 and 6699) or 590 firm-year observations because they are highly regulated firms with different capital structures which are non-comparable to non-financials. Next, we drop 7 problematic listings (70 firm-years observations), which are cases with atypical listing structures or known data issues (e.g., cross-border re-domiciliation). Next, we remove 29 firms already rated at the baseline i.e. in 2014. Finally, we delete 99 pre-listing filler rows auto generated by AIDA for firms that were listed during our sample period. We retain firms that delist during our sample period. Further 1,457 firm-year observations are removed due to the unavailability of the necessary data. The resulting panel comprises 373 firms and 2,508 firm-years, which we use to construct the matched treatment–control sample.

We define our treatment group as firms that receive an ESG rating for the first time during our sample period, that is, between 2013 and 2023. The control group consists of firms that have never received an ESG rating throughout the sample period. In practice, the ESG rating coverage expanded over time. Typically, larger and more visible firms got rated earlier while smaller firms might still be unrated by 2023. We take include only listed firms because very small private firms would not be rated and are not comparable.

3.3. Treatment Definition: ESG Rating Initiation

We define the treatment event at the firm level as the first fiscal year a firm receives an ESG rating from LSEG (formerly Refinitiv). Let *FIRSTESGYEAR* denote the first fiscal year in which firm *i* is assigned an overall ESG score by LSEG. We then define a post-treatment indicator, *ESGPOST*, that equals 1 for treated firms in year *FIRSTESGYEAR* and in all subsequent years, and equals 0 for treated firms in all years prior to *FIRSTESGYEAR*. For firms that are never rated during the sample period (the control firms), *ESGPOST* is 0 in all years. We model ESG coverage as an absorbing state: once a firm becomes ESG-rated, it is treated as continuously covered thereafter.

Our empirical design focuses on coverage initiation rather than rating levels. A growing literature documents substantial disagreement across ESG rating providers, driven by differences in scope, measurement, and weighting which renders rating levels inherently vendor-specific and not directly comparable across agencies (Berg, Kölbel, and Rigobon, 2022). and this disagreement is itself priced in equity markets (Avramov, Cheng, Lioui, and Tarelli, 2022). Ratings levels are therefore vendor-specific and not directly comparable across agencies or over time. By contrast, rating initiation is a discrete and clearly identifiable event that marks the firm's entry into a standardized ESG information environment that is observable to institutional investors, banks, and intermediaries relying on widely used ESG datasets. Subsequently, this may improve cross-firm comparability and lower the information frictions (Christensen, Hail, and Leuz, 2021; Avramov et al., 2022).

LSEG constructs its ESG scores from publicly available materials, such as annual reports, regulatory filings, and sustainability disclosures, processed through a structured, largely rule-based methodology. Coverage expansion is driven by the provider's editorial strategy and by observable firm characteristics such as size, index inclusion, and disclosure availability, rather than by firm request. LSEG does not operate under an issuer-pays model and its score production is operationally separated from its commercial activities, consistent with its stated compliance with the ICMA Code of Conduct for ESG Ratings and Data Product Providers. These institutional features mitigate, but do not eliminate, concerns that coverage is correlated with unobservable firm characteristics that also affect borrowing costs.

Because the drivers of LSEG coverage i.e., size, visibility, disclosure quality, are themselves correlated with credit risk and the cost of debt, we do not treat rating initiation as strictly exogenous. Our identification strategy addresses this selection concern in three ways. First, we construct a matched control group using propensity-score matching on pre-treatment firm size and age within NACE one-digit industries. Second, we estimate a staggered difference-in-differences model using Callaway and Sant'Anna (2021) which allows the treatment effect to vary across adoption cohorts and over event time and remains consistent under treatment-effect heterogeneity. Third, we validate the parallel-trends assumption using pre-treatment event-study coefficients and conduct placebo-based reassignment tests. Under these conditions, we interpret the estimated ATT as the causal effect of ESG rating initiation on the cost of debt, conditional on the identifying assumptions.

3.4. Measuring Dependent Variables

Our dependent variable, the cost of debt (*COD*), is defined as the ratio of annual financial charges to total interest-bearing debt in the same fiscal year. Interest expenses are reported in AIDA under “financial charges” which include the interest expenses and closely related financing costs recognized in the income statement over the year. In practice, these include interest paid on bank loans and overdrafts, coupon interest on bonds (including current portions), charges on convertible bonds, and comparable interest items tied to other borrowings and credit lines. The scale, total interesting-bearing debt, is the sum of all liabilities with explicit interest in the balance sheet. Specifically, we include short and long-term bonds, short and long-term convertible bonds, short and long-term bank borrowings (including overdrafts), amounts due to other lenders, debts to financial institutions, and intragroup or parent-company loans.

To maintain economic plausibility, we set observations with a computed cost of debt (*COD*) above 20% to missing. We do so because values above 20% are unlikely for listed non-financial firms and typically reflect classification anomalies or one-off financing charges rather than the recurring price of debt.

3.5. Matching Procedure and Balance Test

Firms that obtain ESG ratings are not randomly selected and may differ ex-ante from unrated firms. To address this selection on observables, we implement propensity score matching (PSM) and form a control group comparable to treated firms on important observables. Specifically, we estimate a probit of treated on the firm size (*LN_ASSET*) and log of firm (AGE). We apply nearest-neighbour matching with a caliper of 0.08. In the baseline 1:1 specification, matching is performed without replacement, whereas in the 1:3 and 1:5 specifications it is performed with replacement. This approach achieves good covariate balance while retaining as many treated firms as possible. Matching is performed within the same one-digit NACE industry1 and using covariates measured one year before treatment. Our baseline difference-in-differences (DiD) uses the one-to-one matched sample. However, for robustness of the results, we re-estimate all models using one-to-three and one-to-five matched sample.

Table 1 presents the covariate balance statistics before and after propensity score matching. Panel A reports the means, standardized mean differences (%bias), and t-tests for differences in means for our two key covariates i.e., log of firm size (*LN_ASSET*) and log of firm age (*LN_AGE*). The results show a strong balance. For firm size (*LN_ASSET*), the absolute standardized mean difference falls from 129.7% pre-match to 3.2% post-match. The post-match difference is statistically indistinguishable from zero, with a t-value(p-value) of 0.24(0.810). For log of firm age (*LN_ASSET*), the standardized mean difference reduces from 13.3% to 5.0%, again with no significant residual difference with a t-value(p-value) of 0.340(0.738).

Panel B of Table 1 summarizes the overall balance using Rubin's diagnostics which corroborate these findings. The pseudo-R^2 declines from 0.180 to 0.001 and the likelihood-ratio χ^2 statistic falls to 0.14 ($p = 0.934$) and with Rubin's B of 6.1 which is less than 25 and Rubin's R of 1.20, which is between the acceptable range of 0.5 and 2. The post-match variance ratios is 0.72

[1] We use NACE 1 digit instead of NACE 2 or 4 digits to avoid over-restriction.

which is slightly below one but well within commonly accepted bounds of between 0.5 to 2 for adequate balance, consistent with Rubin's guidelines as summarized by Stuart (2010).

[Insert Table 1 here]

3.6. Empirical Methodology

Our main empirical strategy is the multi-period difference-in-differences estimator of Callaway and Sant'Anna (2021), which is designed for settings with staggered treatment adoption, which is the case with ESG ratings of the firms. Let Y_{it}denote the cost of debt (*COD*) for firm i in year t, and let $G_i = g$ be the calendar year in which firm i First receives an ESG rating (with $G_i = \infty$ for never-treated firms).

The Callaway–Sant'Anna framework estimates group-time average treatment effects on the treated, $\text{ATT}_{g,t}$, which compare firms that first become ESG-rated in year g with an appropriate control group of firms that are untreated in year t.

$$\text{ATT}_{g,t} = \mathbb{E}[Y_{it}(1) - Y_{it}(0) \mid G_i = g], t \geq g,$$

where $Y_{it}(1)$ and $Y_{it}(0)$ are the potential COD outcomes with and without an ESG rating, respectively. Aggregating these group-time effects delivers an overall average treatment effect on the treated (ATT) and window-specific ATTs. We also construct pre- and post-treatment averages of the dynamic ATTs to assess the parallel-trends assumption and the persistence of the effect.

We implement the estimator using the doubly robust inverse-probability weighting procedure of Sant'Anna and Zhao (2020), which remains consistent if either the propensity-score model for treatment timing or the outcome-regression model is correctly specified. For the main analysis, we used one-to-one matched sample and repeat the analysis using one-to-three and one-to-five matched samples in the robustness section.

In our analysis, we include firm fixed effects to absorb time-invariant unobservables, year fixed effects to capture common macro–financial conditions (e.g., monetary policy and credit cycle swings) and industry fixed effects at the one-digit NACE level. We cluster the standard errors at the firm level to account for serial correlation.

As robustness checks within the same framework, we use (i) "not-yet-treated" group as an alternative comparison set, (ii) compute wild-bootstrap standard errors, and (iii) re-estimate the ATT using the two other estimators proposed by Callaway and Sant'Anna which includes inverse-probability weighting and outcome regression. We also re-estimate the dynamic treatment effects using the interaction-weighted event-study estimator of Sun and Abraham (2021).

4. Empirical Analysis

4.1. Descriptive Statistics

Appendix A.3 reports the distribution of firm-year observations by calendar year (Panel A) and by one-digit NACE industry (Panel B). The number of observations ranges from 211 in 2014 (8.41% of the sample) to a maximum of 297 in 2022 (11.84%). This pattern reflects a general increase in the coverage of listed firms over the sample period. On average, there are 251 firm-year observations in our sample from 2013 to 2023. The sample is slightly over-represented by "mining and quarrying" (code 2) with 26.40% of total firm-year observations and information and communication (code 7) with 21.45% of total firms-year observations. On the other side, public administration and defence (code 8) and other services (code 9) are under-represented. The rest of the industries contribute between 7 to 14% of the total firms-year observations. The industry composition is in line with the structure of the Italian economy where manufacturing, extraction, and technology sectors are prominent among publicly listed firms.

Table 2 reports the summary statistics based on the full sample across 2,508 firm-year observations. The mean (median) cost of debt (*COD*) is 4.1% (3.4%). Profitability is modest, with a mean (median) return on assets (*ROA*) of 4.1% (4.5%). The full-sample's mean (median) firm age (*AGE) is* 28.9 (23). In our sample, 29.4% of firm-years belong to firms that are ever treated (*TREATED*). The panel B of Table 2 shows that treated firms are larger and older, more profitable, less levered, and face a lower *COD*. Specifically, *COD* is about 50 basis points lower for treated firms, leverage is 4.5% lower, and *ROA* is higher. These differences are statistically significant at conventional levels. It is important to note that the treated firms are much larger in size and in age.

The treated firms have an average asset holding of 445 million compared to 238 million of the untreated firms. Similarly, treated firms are, on average, 5.150 years older than untreated firms. These imbalances, especially in size, age, and profitability, makes it important to use a matched sample to avoid biased results.

[Insert Table 2 here]

Table 3 shows the summary statistics for the one-to-one propensity score matched panel, where treated firms are matched to untreated firms one year before the treatment (*t–1*) within the same NACE 1-digit industry. In the matched sample, the mean (median) cost of debt (*COD*) is 4.0% (3.3%), leverage (*LEV*) is 55.2% (55.2%), and return on assets (*ROA*) is 4.8% (8.0%). Relative to the full sample, cross-sectional differences between treated and control firms are substantially reduced in the matched sample across all the variables.

[Insert Table 3 here]

4.2. Testing the Parallel-Trend Assumption

To assess the parallel-trends assumption, we estimate event-study specifications that recover dynamic treatment effects around ESG rating initiation. The identifying assumption is supported if the estimated pre-treatment (lead) coefficients are statistically indistinguishable from zero and display no systematic pattern, while post-treatment (lag) coefficients capture the evolution of the effect after initiation.

We use two complementary estimators to do that which includes the doubly robust method of Callaway and Sant'Anna (2021) and the interaction-weighted approach of Sun and Abraham (2021). The event window is kept at [−5, +5] years relative to first rating. We omit the t = -1 as the baseline in the TWFE and Sun-Abraham models (following Sun and Abraham, 2021; Hansen, Perez, and Shapiro, 2023). However, in the Callaway and Sant’Anna setup, t = -1 is retained by construction. We use the one-to-one matched sample. The specifications remain the same as in the main analysis of these estimators.

Panel B of Table 4 shows that event-time ATTs are close to zero in the pre-treatment period, with no systematic pattern. Panel A of reports a average pre-treatment ATT of 0.002 with a 95% CI [−0.002, 0.003] which is statistically insignificant with a p-value of 0.825. Similarly, a joint test across $t = -5,\ldots,-1$ yields $\chi^2(5) = 3.11$ with a p-value of 0.683. A joint test across $t = -5,\ldots,-1$ yields $\chi^2(5) = 3.11$ ($p = 0.683$). Together with the event-study plot in Figure 1, these results support the parallel-trends assumption.

We obtain similar results using the Sun–Abraham event-study estimates (Appendix A.4). Pre-treatment coefficients ($t = -5,\ldots,-2$) are small and statistically indistinguishable from zero, suggesting no differential pre-trends. A joint test of no pre-trends shows a χ^2 (4) of 2.52 with p-value of 0.642.

The statistical tests of the pretend and visual inspections support the parallel trends assumption. Pre-treatment coefficients are economically small, statistically insignificant, and show no directional pattern.

4.3. Baseline Difference-in-Difference Estimates using Callaway-Sant'Anna (2021)

Panel A of Table 4 reports the average treatment effects on the treated (ATT) from the Callaway and Sant'Anna (2021) model. The overall ATT is –0.009, indicating that after obtaining an ESG rating, the average firm experiences a 90-basis points reduction in its cost of debt (*COD*) relative to its counterfactual path. This effect is statistically significant at the 1% level and economically meaningful, representing roughly a 20% decline compared to the sample mean *COD*. The magnitude of the effect strengthens over time. During the first two years after receiving an ESG rating, the average effect is –0.006 and statistically significant at the 5% level, deepening to –0.013 (5% level) in years 3 to 5 and –0.031 in years 6 to 8. The pre-treatment average ATT is statistically indistinguishable from zero, suggesting no evidence of differential pre-trends between treated and control firms.

Panel B of Table 4 reports the event-time ATTs from −5 to +5 years relative to ESG rating initiation. The coefficients remain close to zero before treatment and become increasingly negative afterward. Statistically significant declines begin two years after initiation and persist through t = +5. For example, the ATT is negative and statistically significant at the 5% level in each of these post-treatment periods, declining from −0.009 in t+2 to −0.011 in t+3, −0.014 in t+4, and −0.015 in t+5.

Panel C of Table 4 reports cohort-specific estimates by first rating year. The effects are generally negative across cohorts, with the largest decline for firms first rated in 2019 (ATT = −0.029). Firms first rated in 2015 and 2017 also exhibit statistically significant reductions (ATT = −0.015 and −0.016, respectively). Panel D of Table 4 reports calendar-year ATTs and shows that effects become more consistently negative in later years, reaching −0.013 by 2023.

[Insert Table 4 here]

[Insert Figure 1 here]

5. Robustness Tests

We conduct several robustness tests. First, we re-estimate our baseline Callaway and Sant'Anna model using 1:3 and 1:5 propensity-score matched samples (see Panel A and B of Table 5) to test whether our estimates are driven by the specific matching design. Across these alternative matches, the estimated ATT on *ESGPOST* remains negative and statistically significant, with magnitudes very similar to the baseline. This shows that the estimated reduction in the cost of debt is not sensitive to the choice of matching ratio or to the construction of the control group.

Next, within the Callaway–Sant'Anna framework, in addition to the doubly robust IPW, we use inverse-probability weighting and outcome regression (Panel C of Table 5). These two procedures produce very similar ATTs of roughly –0.009, significant at the 1% level, confirming that the documented decline in the cost of debt is not driven by functional-form assumptions in the propensity-score or outcome models.

Within the multi-period DiD framework of Callaway and Sant'Anna (2021), we also switch the comparison group from "never treated" to "not-yet-treated" firms and compute wild-bootstrap standard errors. Panel D of Table 5 shows the resulting ATTs are virtually unchanged and remain statistically significant indicating that our conclusions do not depend on the comparison group or on asymptotic standard error approximations.

Next, we re-estimate dynamic effects using the interaction-weighted event-study estimator of Sun and Abraham (2021). Appendix A.4 reports the estimates. Pre-treatment coefficients are small and statistically indistinguishable from zero, while post-treatment coefficients become increasingly negative over event time. These results mirror those from the Callaway-Sant'Anna estimation method.

Next, we test whether our ESG-rating effect could arise from spurious correlation or common shocks using a placebo design based on the Callaway and Sant'Anna (2021) estimator. We first remove all observations at and after the true ESG-rating year of treated firms, so that treated firms only contribute pre-rating years and never-rated firms retain their full histories. Within this placebo sample, we randomly assign a pseudo first ESG-rating year within each firm's observed window to roughly half of the never-rated firms, leaving the rest (and all originally treated firms) as controls. Using these pseudo initiation years, we re-estimate the same Callaway–Sant'Anna multi-period DiD model on the matched sample and repeat this procedure 500 times, storing the overall ATT and its 95% confidence interval for each draw.

Figure 2 plots the ordered placebo ATTs with their confidence intervals and flags the few spuriously significant estimates. The placebo effects are tightly centered around zero, with only a handful of significant outliers and no systematic negative pattern comparable to our main estimates. This indicates that the observed decline in COD after the first ESG rating is unlikely to be driven by random assignment or generic features of the data.

Overall, these robustness tests strengthen our conclusion that ESG rating initiation is followed by a persistent and statistically reliable decline in firms' cost of debt. The result is robust to alternative matching ratios, alternative estimators and comparison groups within the multi-period DiD framework, and placebo-style reassignment tests.

[Insert Table 5 here]

[Insert Figure 2 here]

6. Heterogeneity Analysis

We study whether the impact of becoming ESG-rated on the cost of debt varies across firms by re-estimating the Callaway and Sant'Anna (2021) estimator within matched subsamples split by asset tangibility, financial constraints (SA index), leverage, industry carbon intensity (green vs brown), and firm size. Table 6 reports the overall post-treatment ATT, the average pre-treatment ATT, and window specific ATTs for 0–2, 3–5, and 6–8 years after the first ESG rating. Across splits, the general trend is that becoming ESG-rated tends to reduce the cost of debt whereas this reduction grows over time. In most subsamples the overall post-treatment ATT is negative and statistically and economically meaningful and the 3–5 and 6–8-year windows show larger effects than the 0–2-year window. This is consistent with lenders gradually incorporating ESG ratings into internal models and contract terms. Pre-treatment ATTs are small and statistically insignificant across splits, indicating no systematic pre-trends within subgroups and supporting the identification strategy.

Panel A of Table 6 shows the subsample split by financial constraints. Firms having high financial constraint (above median SA index) benefit much more from ESG rating initiation. For these firms, post-treatment ATTs are larger in absolute value and emerge earlier whereas unconstrained firms exhibit smaller and more gradual effects. This is consistent with the view that an ESG ratings acts as a certification device that relaxes financing frictions. When firms are financially constrained, lenders' concerns about adverse selection and information risk are more severe (Stiglitz & Weiss, 1981). A third-party ESG evaluation reduces estimation risk by transforming non-financial practices into standardized and auditable metrics which likely eases rationing and lowers the required spreads.

Panel B of Table 6 shows the subsample split by leverage. We find that highly levered firms exhibit a stronger and earlier reduction in the cost of debt than low leverage firms. For borrowers close to distress thresholds, lenders are particularly sensitive to any signal that helps distinguish high from low quality risk. ESG ratings provide precisely such a separating signal, indicating better risk management, stakeholder relations, and governance. This, in return, narrows the spread on highly levered firms. This result is in line with the broader certification literature where more informative ratings and external assessments improve credit market access and reduce borrowing costs (Tang, 2009; Attig et al., 2013).

Panel C of Table 6 shows that firms with high tangibility experience a sizable and statistically significant reduction in borrowing costs after getting an ESG rating with effects deepening over time. Low tangibility firms show no robust average decline. This is consistent with the idea that ESG ratings being most valuable when they address material risks embedded in physical capital. Capital-intensive firms, often in environmentally exposed sectors, face ESG-related liabilities and regulatory scrutiny that directly enter banks' risk assessments. For them, ESG rating supplies verifiable evidence on environmental and governance practices that can be fed into internal models and ESG-risk frameworks, leading to lower spreads. By contrast, asset-light firms rely more on intangibles and relationship lending where an ESG score adds less incremental hard information relative to existing soft information and is less central to regulatory classification.

Panel D of Table 6 presents the split by industry-level ESG exposure. Firms operating in green (i.e., low CO_2 intensive) industries experience a noticeably stronger and more precisely estimated reduction in borrowing costs after receiving an ESG rating. Firms in brown (i.e., high CO_2 intensive) industries also show meaningful but smaller declines. The larger effect for green firms is consistent with the idea that bank's view loans to ESG-aligned industries as especially valuable. When a green sector firm becomes ESG-rated, banks can more easily classify the loan as part of their green or sustainability-linked lending activities and demonstrate compliance with ECB/EBA expectations on ESG risk integration. This increase the internal value of such loans to banks, lowers their own funding or capital costs, and allows part of these gains to be passed on to borrowers through lower spreads. For brown industries, an ESG rating still reduces cost of debt likely because it helps lenders differentiate better-managed brown firms and provides evidence of credible transition efforts. However, these firms continue to carry higher underlying environmental and regulatory risk. As a result, the cost-of-debt reduction for brown industries is negative but mechanically capped relative to green industries.

Panel E of Table 6 shows that both large and small firms benefit from ESG rating initiation but likely for different reasons tied to the types of risks lenders price. For small firms, credit risk is driven heavily by opacity, limited collateral, and asymmetric information. An ESG rating likely acts as a reputation building device that reduces uncertainty about management quality and long-term risk orientation which helps the lenders to re-assess default risk more favourably. For large firms, credit risk is less about information frictions and likely more about institutional considerations. The loans from large firms are often large and syndicated. Because banks often include large-firm loans in their ESG-focused lending portfolios, these loans become more attractive to hold once the firm receives an ESG rating. When a large firm becomes ESG-rated, it increases the bank's ability to classify the exposure as ESG-consistent for regulatory and funding purposes. This in turn reduces the bank's own cost of capital and is then passed through to borrowers.

Overall, the heterogeneity results reinforce our interpretation of ESG rating initiation as an informational activation event. The effect is strongest where ex ante risk and financing frictions are greater, where assets and industries are more exposed to ESG-related risks, and where regulatory and portfolio-allocation considerations make standardized ESG information especially valuable to banks. This pattern is precisely what one would expect if ESG ratings reduce information asymmetry.

[Insert Table 6 here]

7. Conclusions

We study the effect of ESG rating initiation on firms' cost of debt for Italian listed non-financial firms over 2013–2023. Using a staggered-adoption multi-period DiD approach, we find that receiving an ESG rating is followed by a statistically and economically significant decline in borrowing costs. On average, ESG rating initiation is associated with about a 90-basis-point decline in the cost of debt, with the reduction growing over time and no evidence of differential pre-trends. The result is robust to alternative matching ratios, estimators, comparison groups, and placebo-style tests. The effect is stronger for financially constrained and highly levered firms and is more pronounced among capital-intensive firms and firms in greener industries.

These findings have practical and academic implications. By showing that ESG rating initiation causally lowers firms' cost of debt, our study contributes to the debt financing literature on non-financial determinants of debt pricing. It also contributes to the ESG-pricing literature by documenting that ESG information is priced by creditors (not only equity investors) within the Italian/EU sustainable-finance context, and to disclosure and information-economics work by suggesting that third-party ESG ratings can reduce information asymmetry. Practically, credible ESG coverage can be associated with meaningful interest-cost savings for firms, especially under tighter financing conditions, while helping lenders and investors in screening and risk-based pricing. For policymakers and standard setters, the results support the view that improving the availability and standardization of ESG information can have real financing consequences.

Future research could build on these findings by more directly isolating the underlying mechanisms. For example, it will be interesting to use loan- or bond-level data to pinpoint which contractual features adjust in response to ESG rating initiation, such as credit spreads, maturities, or covenant tightness. Extending the study to additional countries and alternative ESG rating providers would clarify how generalizable the results are and investigating changes in regulation as well as divergence across rating agencies could reveal the conditions and borrower types for which ESG signals are most influential in credit pricing.

References

Asimakopoulos, P., Asimakopoulos, S., & Li, X. (2023). The role of environmental, social, and governance rating on corporate debt structure. Journal of Corporate Finance, 83, 102488.

Attig, N., El Ghoul, S., Guedhami, O., & Suh, J. (2013). Corporate social responsibility and credit ratings. *Journal of Business Ethics, 117*(4), 679–694.

Avramov, D., Cheng, S., Lioui, A., & Tarelli, A. (2022). Sustainable investing with ESG rating uncertainty. Journal of Financial Economics, 145(2), 642–664.

Berg, F., Kölbel, J. F., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. Review of Finance, 26(6), 1315–1344.

Berger, A. N., & Udell, G. F. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of Banking & Finance*, 22(6–8), 613–673.

Boot, A. W. A. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation*, 9(1), 7–25.

Bikmetova, N., & Pirinsky, C. A. (2026). Do ESG rating agencies improve ESG performance? Journal of Business Ethics, 204, 335–365.

Bloomberg. (2024, February 8). *Global ESG assets predicted to hit $40 trillion by 2030, despite challenging environment, forecasts Bloomberg Intelligence*. https://www.bloomberg.com/company/press/global-esg-assets-predicted-to-hit-40-trillion-by-2030-despite-challenging-environment-forecasts-bloomberg-intelligence/

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics, 225*(2), 200–230.

Cantor, R., & Packer, F. (1996). Determinants and impact of sovereign credit ratings. Economic Policy Review, 2(2).

Capasso, G., Gianfrate, G., & Spinelli, M. (2020). Climate change and credit risk. *Journal of Cleaner Production*, 266, 121634.

Chemmanur, T. J., & Fulghieri, P. (1994). Reputation, renegotiation, and the choice between bank loans and publicly traded debt. *Review of Financial Studies*, 7(3), 475–506.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science*, 60(9), 2223–2247.

Cheng, B., Ioannou, I., & Serafeim, G. (2014). Corporate social responsibility and access to finance. *Strategic Management Journal*, 35(1), 1–23.

Christensen, H. B., Hail, L., & Leuz, C. (2021). Mandatory CSR and sustainability reporting: Economic analysis and literature review. Review of Accounting Studies, 26, 1176–1248.

Delis, M. D., Greiff, K., Iosifidi, M., & Ongena, S. (2024). Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans. *Financial Markets, Institutions & Instruments, 33*, 239–265.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *Review of Economic Studies*, 51(3), 393–414.

EBA. (2023). *Final Report on the management and supervision of ESG risks for credit institutions and investment firms*. European Banking Authority, Paris.

ECB. (2022). *Guide on climate-related and environmental risks: Supervisory expectations relating to risk management and disclosure*. European Central Bank, Frankfurt.

El Ghoul, S., Guedhami, O., Kwok, C. C. Y., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance*, 35(9), 2388–2406.

Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*, 142(2), 499–516.

Francis, J., LaFond, R., Olsson, P., & Schipper, K. (2005). The market pricing of accruals quality. *Journal of Accounting and Economics*, 39(2), 295–327.

Freyaldenhoven, S., Hansen, C., Pérez Pérez, J., & Shapiro, J. M. (2022). Visualization, identification, and estimation in the linear panel event study design. Working Papers 2022-07, Banco de México.

Goss, A., & Roberts, G. S. (2011). The impact of corporate social responsibility on the cost of bank loans. *Journal of Banking & Finance*, 35(7), 1794–1810.

Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies, 23*(5), 1909–1940.

Hasan, I., Hoi, C. K., Wu, Q., & Zhang, H. (2017). Social capital and debt contracting: Evidence from bank loans and public bonds. *Journal of Financial and Quantitative Analysis*, 52(3), 1017–1047.

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(1–3), 405–440.

IOSCO. (2021). Environmental, Social and Governance (ESG) ratings and data products providers: Final report. International Organization of Securities Commissions. https://www.iosco.org/library/pubdocs/pdf/IOSCOPD690.pdf

Javadi, S., & Masum, A.-A. (2021). The impact of climate change on the cost of bank loans. Journal of Corporate Finance, 69, 102019.

Kisgen, D. J. (2006). Credit ratings and capital structure. Journal of Finance, 61(3), 1035–1072.

Kisgen, D. J., & Strahan, P. E. (2010). Do regulations based on credit ratings affect a firm's cost of capital? *Review of Financial Studies*, 23(12), 4324–4347.

Kelly, B., & Ljungqvist, A. (2012). Testing asymmetric-information asset pricing models. Review of Financial Studies, 25(5), 1366–1413.

Kraus, A., & Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *Journal of Finance*, 28(4), 911–922.

Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *Journal of Finance*, 72(4), 1785–1824.

Megginson, W. L., & Weiss, K. A. (1991). Venture capitalist certification in initial public offerings. *Journal of Finance*, 46(3), 879–903.

Menz, K.-M. (2010). Corporate social responsibility: Is it rewarded by the corporate bond market? A critical note. *Journal of Business Ethics*, 96(1), 117–134.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2), 187–221.

Ng, A. C., & Rezaee, Z. (2015). Business sustainability performance and cost of equity capital. *Journal of Corporate Finance*, 34, 128–149.

Oikonomou, I., Brooks, C., & Pavelin, S. (2014). The effects of corporate social performance on the cost of corporate debt and credit ratings. *Financial Review*, 49(1), 49–75.

Sant'Anna, P. H. C., & Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics, 219*(1), 101–122.

Sengupta, P. (1998). Corporate disclosure quality and the cost of debt. *Accounting Review*, 73(4), 459–474.

Sharfman, M. P., & Fernando, C. S. (2008). Environmental risk management and the cost of capital. *Strategic Management Journal*, 29(6), 569–592.

Spence, M. (1973). Job market signaling. *Quarterly Journal of Economics*, 87(3), 355–374.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review*, 71(3), 393–410.

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics, 225*(2), 175–199.

Tang, T. T. (2009). Information asymmetry and firms' credit market access: Evidence from Moody's credit rating format refinement. *Journal of Financial Economics*, 93(2), 325–351.

Tables

Table 1: PSM Balance Test

Panel A: Covariate Balance Before and After Matching

Variable	Status	Mean (Treated)	Mean (Control)	% Bias	% Bias Reduction	t-stat	p-value	Variance Ratio
LN_ASSET	Unmatched	12.967	11.041	129.7		10.35	0.00	0.44*
LN_ASSET	Matched	12.747	12.699	3.20	97.5	0.24	0.81	0.98
LN_FIRMAGE	Unmatched	3.1137	2.9991	13.3		1.23	0.220	0.97
LN_FIRMAGE	Matched	3.2301	3.1874	5.00	62.7	0.34	0.738	1.04

Panel B: Global Balance Diagnostics (Rubin's Tests)

Sample	Pseudo-R^2	LR χ^2	p-value	Mean Bias	Med Bias	Rubin's B	Rubin's R
Unmatched	0.180	133.35	0.000	71.5	71.5	134.6*	0.5*
Matched	0.001	0.14	0.934	4.1	4.1	6.1	1.20

The table reports covariate-balance diagnostics before and after propensity-score matching (PSM). Panel A lists treated and control means, the standardized mean difference (% Bias), which is the treated–control mean difference scaled by the pooled standard deviation and expressed as a percentage, two-sample t-tests for equality of means, p-values, and the variance ratio. Panel B summarizes global balance from the PSM model. It provides the Pseudo-R^2 and the LR χ^2 test of joint significance of covariates, Rubin's B which is the absolute standardized difference in the mean propensity score and Rubin's R which is the ratio of the treated-to-control propensity-score variances. Asterisks flag values outside or right at the boundary of common rules-of-thumb. That is, for variance ratios outside 0.8–1.25, Rubin's B > 25, and Rubin's R $\notin$ [0.5, 2].

Table 2: Summary statistics of key variables for treated and control firms using the full sample

Panel A: Summary Statistics using Full Sample

Variable	Mean	SD	P25	Median	P75	Min	Max	Obs
COD	0.041	0.030	0.020	0.034	0.053	0.000	0.200	2508
TREATED	0.294	0.456	0.000	0.000	1.000	0.000	1.000	2508
ESGPOST	0.165	0.372	0.000	0.000	0.000	0.000	1.000	2508
LEV	0.579	0.185	0.461	0.576	0.701	0.034	1.000	2508
LN_SALES	11.392	1.924	10.167	11.333	12.754	1.910	16.311	2508
ROA	0.041	0.091	0.013	0.045	0.083	-0.375	0.437	2508
AGE	28.897	23.458	13.000	23.000	37.000	0.000	146.000	2508
LN_AGE	3.107	0.813	2.639	3.178	3.638	0.000	4.990	2508

Panel B: Summary statistics by treated and control firms using the full sample

	Treated			Untreated			Mean Diff Test		
	Mean	SD	Obs	Mean	SD	Obs	Mean Diff	p-val	t-val
COD	0.038	0.028	738	0.043	0.031	1770	-0.005	0.000	3.909
ESGPOST	0.562	0.496	738	0.000	0.000	1770	0.562	0.000	-47.669
LEV	0.547	0.151	738	0.592	0.196	1770	-0.045	0.000	5.517
LN_SALES	13.027	1.500	738	10.711	1.651	1770	2.316	0.000	-32.860
ROA	0.063	0.071	738	0.033	0.097	1770	0.030	0.000	-7.527
AGE	32.531	24.615	738	27.381	22.795	1770	5.150	0.000	-5.034
LN_AGE	3.245	0.793	738	3.050	0.815	1770	0.195	0.000	-5.519

This table reports descriptive statistics for the main variables used in the analysis, based on the full sample of Italian publicly listed non-financial firms from 2013 to 2023 after applying necessary filtration as specified in Appendix A_. Panel A presents the means, medians, standard deviations, minimum, maximum and the number of firm-year observations for all variables. Panel B reports the differences in means and medians between ESG-rated (treated) and non-rated (control) firm-years. The sample includes both ESG-rated (treated) and non-rated (control) firms. The cost of debt (*COD*) is defined as total interest expense divided by total interest-bearing debt. *ESGPOST* is the post-treatment indicator, which equals 1 for all years greater than or equal to the first calendar year in which a firm receives its first ESG rating from LSEG, and 0 otherwise. *AT* denotes the total assets of a firm (in thousands). *LNSALES* is the logarithm of total sales, used as a proxy for firm size. *ROA* (return on assets) is computed as net income divided by total assets. *LN_AGE* represents the logarithm of a firm's age (years since incorporation). All variables are defined in Appendix A2. The last two columns report differences in the mean and median between treated and control firm-years. The significance level for the difference in means is based on a two-sample t-test assuming equal variances, while the significance level for the difference in medians is based on the Wilcoxon rank-sum (Mann–Whitney) test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Summary statistics of key variables for treated and control firms using the matched sample

Panel A: Summary Statistics using Matched Sample

Variable	Mean	SD	P25	Median	P75	Min	Max	Obs
COD	0.040	0.028	0.020	0.033	0.051	0.000	0.200	1024
TREATED	0.570	0.495	0.000	1.000	1.000	0.000	1.000	1024
ESGPOST	0.310	0.463	0.000	0.000	1.000	0.000	1.000	1024
LEV	0.552	0.174	0.448	0.552	0.665	0.034	1.000	1024
LN_SALES	12.294	1.695	11.437	12.434	13.345	1.910	16.044	1024
ROA	0.048	0.080	0.020	0.049	0.089	-0.375	0.437	1024
AGE	32.957	25.384	16.000	27.000	41.000	0.000	146.000	1024
LN_AGE	3.276	0.730	2.833	3.332	3.738	0.000	4.990	1024

Panel B: Summary statistics by treated and control firms using the matched sample

	Treated			Untreated			Mean Diff Test		
	Mean	SD	Obs	Mean	SD	Obs	Mean Diff	p-val	t-val
COD	0.037	0.027	584	0.043	0.030	440	-0.005	0.002	3.035
ESGPOST	0.543	0.499	584	0.000	0.000	440	0.543	0.000	-22.834
LEV	0.547	0.154	584	0.560	0.197	440	-0.012	0.258	1.133
LN_SALES	12.791	1.530	584	11.634	1.680	440	1.157	0.000	-11.480
ROA	0.065	0.076	584	0.025	0.079	440	0.040	0.000	-8.198
AGE	35.207	25.820	584	29.970	24.504	440	5.237	0.001	-3.284
LN_AGE	3.353	0.717	584	3.174	0.736	440	0.179	0.000	-3.913

This table reports descriptive statistics for the main variables used in the analysis, based on the one-to-one propensity-score matched sample of Italian publicly listed non-financial firms from 2013 to 2023. Panel A presents the means, medians, standard deviations, minimum, maximum and the number of firm-year observations for all variables. Panel B reports the differences in means and medians between ESG-rated (treated) and non-rated (control) firm-years. The sample includes both ESG-rated (treated) and non-rated (control) firms. The cost of debt (*COD*) is defined as total interest expense divided by total interest-bearing debt. *ESGPOST* is the post-treatment indicator, which equals 1 for all years greater than or equal to the first calendar year in which a firm receives its first ESG rating from LSEG, and 0 otherwise. *AT* denotes the total assets of a firm (in thousands). *LNSALES* is the logarithm of total sales, used as a proxy for firm size. *ROA* (return on assets) is computed as net income divided by total assets. *AGE* represents the logarithm of a firm's age (years since incorporation). All variables are defined in Appendix A.2. The last two columns report differences in the mean and median between treated and control firm-years. The significance level for the difference in means is based on a two-sample t-test assuming equal variances, while the significance level for the difference in medians is based on the Wilcoxon rank-sum (Mann–Whitney) test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: ESG Rating and the Cost of Debt: Callaway–Sant'Anna (2021) Difference-in-Differences Estimates

Panel A: Overall and Windowed Effects

	ATT
Overall ATT	-0.009***
	(0.003)
Post 0–2 years (avg)	-0.006**
	(0.003)
Post 3–5 years (avg)	-0.013***
	(0.005)
Post 6–8 years (avg)	-0.031***
	(0.008)
Pre-average	0.002
	(0.002)

Panel B: Event Study: Dynamic Effects of ESG Rating Initiation on the COD

	ATT on *COD*
Tm5	-0.001
	(0.006)
Tm4	0.005
	(0.004)
Tm3	0.003
	(0.005)
Tm2	-0.004
	(0.005)
Tm1	-0.002
	(0.003)
Tp0	-0.003
	(0.003)
Tp1	-0.005
	(0.003)
Tp2	-0.009**
	(0.004)
Tp3	-0.011**
	(0.005)
Tp4	-0.014**
	(0.006)
Tp5	-0.015**
	(0.007)
Observations	1,000

Panel C: ATT by Cohort

Cohort	ATT
GAverage	-0.009***
	(0.003)
G2015	-0.015***
	(0.003)
G2016	0.001
	(0.003)
G2017	-0.016***
	(0.005)
G2018	-0.007
	(0.006)
G2019	-0.029**
	(0.012)
G2020	-0.005
	(0.004)
G2021	-0.008**
	(0.004)

Panel D: ATT by Calendar Year

Year	ATT
CAverage	-0.006***
	(0.002)
T2015	-0.009***
	(0.003)
T2016	0.002
	(0.007)
T2017	0.000
	(0.004)
T2018	-0.001
	(0.004)
T2019	-0.005
	(0.006)
T2020	-0.008*
	(0.004)
T2021	-0.011**
	(0.004)
T2022	-0.012**
	(0.005)
T2023	-0.013**
	(0.006)

This table reports the estimated effect of obtaining an ESG rating on firms' cost of debt (*COD*) using the multi-period difference-in-differences estimator of Callaway and Sant'Anna (2021). Panel A reports average treatment effects on the treated (ATT). "Overall ATT" is the average post-treatment effect across all years. "Post 0–2", "Post 3–5", and "Post 6–8" show average effects within the corresponding post-treatment windows. "Pre-average" is the mean of the pre-treatment coefficients and provides a summary check of the parallel-trends assumption, while "Post-average" is the mean effect over all post-treatment years. Panel B presents dynamic event-time ATTs around the first ESG rating.

T_mm and T_pp denote the effect *m* periods before and *p* periods after the first ESG rating is obtained, respectively, with Tp0 denoting the year the rating is obtained. Estimates are obtained using the doubly-robust inverse-probability-weighted version of the Callaway–Sant'Anna estimator. Panel C reports cohort-specific ATTs by year of first ESG rating (G2015–G2021), with "GAverage" denoting the average effect across all treated cohorts. Panel D reports calendar-year ATTs by year of observation (T2015–T2023), with "CAverage" denoting the average effect across all post-treatment calendar years. Standard errors, reported in parentheses, are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Robustness Tests

Panel A. Effect of ESG Rating on Cost of Debt – Matched Sample 1-to-3

	Post-treated ATT	Pre-treated ATT	Post 0–2 years	Post 3–5 years	Post 6-8 years
ATT	-0.010***	0.001	-0.007***	-0.014***	-0.027***
	(0.003)	(0.002)	(0.002)	(0.005)	(0.009)

Panel B. Effect of ESG Rating on Cost of Debt – Matched Sample 1-to-5

	Post-treated ATT	Pre-treated ATT	Post 0 to 2 years	Post 3 to 5 years	Post 6 to 8 years
ATT	-0.010***	0.001	-0.006**	-0.013***	-0.028***
	(0.003)	(0.002)	(0.002)	(0.005)	(0.009)

Panel C: Different estimators

	IPW	REG	DR-IPW
ATT	-0.009***	-0.009***	-0.009***
	(0.003)	(0.003)	(0.003)
Observations	1000	1000	1000

Panel D: Wild-Bootstrapping with NotYet option

	Post-treated ATT	Pre-treated ATT	Post 0 to 2 years	Post 3 to 5 years	Post 6 to 8 years
ATT	0.002	-0.005**	-0.013***	-0.031***	-0.009***
	(0.001)	(0.003)	(0.005)	(0.008)	(0.003)

Panel E: Re-estimation using Sun-Abaraham method

	Post-treated ATT	Pre-treated ATT	Post 0 to 2 years	Post 3 to 5 years	Post 6 to 8 years
ATT	-0.013***	-0.008**	-0.014***	-0.017*	0.003
	(0.004)	(0.003)	(0.005)	(0.009)	(0.004)

This table reports the results of different robustness tests. Panel A shows the average treatment effects on the treated (ATT) of obtaining a first ESG rating on firms' cost of debt (COD) using the Callaway and Sant'Anna (2021) multi-period DiD estimator with PSM matched samples of Italian publicly listed non-financial firms over 2013–2023. COD is defined as total interest expense divided by total interest-bearing debt. The treatment date is the first year in which a firm receives an ESG rating from LSEG. Panel A is based on a 1-to-3 nearest-neighbour PSM matched sample while Panel B uses a 1-to-5 matched sample. In Panel A and B, "Post-treated ATT" is the overall average treatment effect across all post-rating years. "Pre-treated ATT" is the mean ATT in the pre-rating period and is reported as a diagnostic for parallel trends. "Post 0–2 years", "Post 3–5 years", and "Post 6–8 years" show horizon-averaged ATTs over the indicated event-time windows relative to the first rating year. Panel C report the average treatment effect on the treated (ATT) of first ESG-rating initiation on the firm's cost of debt (COD) estimated using the Callaway and Sant'Anna (2021) multi-period DiD framework. IPW uses inverse-probability weighting based on the propensity score; REG uses outcome regression; DR-IPW is doubly robust, remaining consistent if either the propensity-score model or the outcome-regression model is correctly specified (Sant'Anna & Zhao, 2020). Reported standard errors are cluster-**robust** (two-sided tests of ATT = 0); significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Heterogeneous Effects of ESG Rating on the Cost of Debt

Panel A: Split by Financial Constraints (High vs. Low SA Index)

	Post-treated ATT	Pre-treated ATT	Post 0–2 years	Post 3–5 years	Post 6-8 years	Obs
High Fin Constraint	-0.017***	0.003	-0.009***	-0.026***	-0.044***	471
	(0.004)	(0.003)	(0.003)	(0.006)	(0.013)	
Low Fin Constraint	-0.004	0.002	-0.004	-0.006	-0.010**	500
	(0.005)	(0.002)	(0.004)	(0.008)	(0.005)	

Panel B – Leverage: High vs Low

	Post-treated ATT	Pre-treated ATT	Post 0–2 years	Post 3–5 years	Post 6-8 years	Obs
High Leverage	-0.011**	0.004**	-0.009**	-0.011	-0.039***	512
	(0.005)	(0.002)	(0.004)	(0.008)	(0.014)	
Low Leverage	-0.008*	-0.001	-0.003	-0.015**	-0.028***	488
	(0.005)	(0.003)	(0.004)	(0.007)	(0.009)	

Panel C: Asset Tangibility (High vs. Low)

	Post-treated ATT	Pre-treated ATT	Post 0–2 years	Post 3–5 years	Post 6-8 years	Obs
High Tangibility	-0.013***	0.001	-0.010***	-0.016**	-0.048***	529
	(0.005)	(0.002)	(0.004)	(0.008)	(0.008)	
Low Tangibility	-0.006	0.004*	-0.001	-0.012**	-0.024***	471
	(0.004)	(0.002)	(0.003)	(0.006)	(0.008)	

Panel D – Industry Carbon Intensity: Green vs Brown Sectors

	Post-treated ATT	Pre-treated ATT	Post 0–2 years	Post 3–5 years	Post 6-8 years	Obs
Brown Industry	-0.010*	-0.002	-0.003	-0.016*	-0.041***	449
	(0.006)	(0.002)	(0.004)	(0.009)	(0.012)	
Green Industry	-0.013***	0.001	-0.009**	-0.017**	-0.043***	385
	(0.005)	(0.003)	(0.004)	(0.007)	(0.007)	

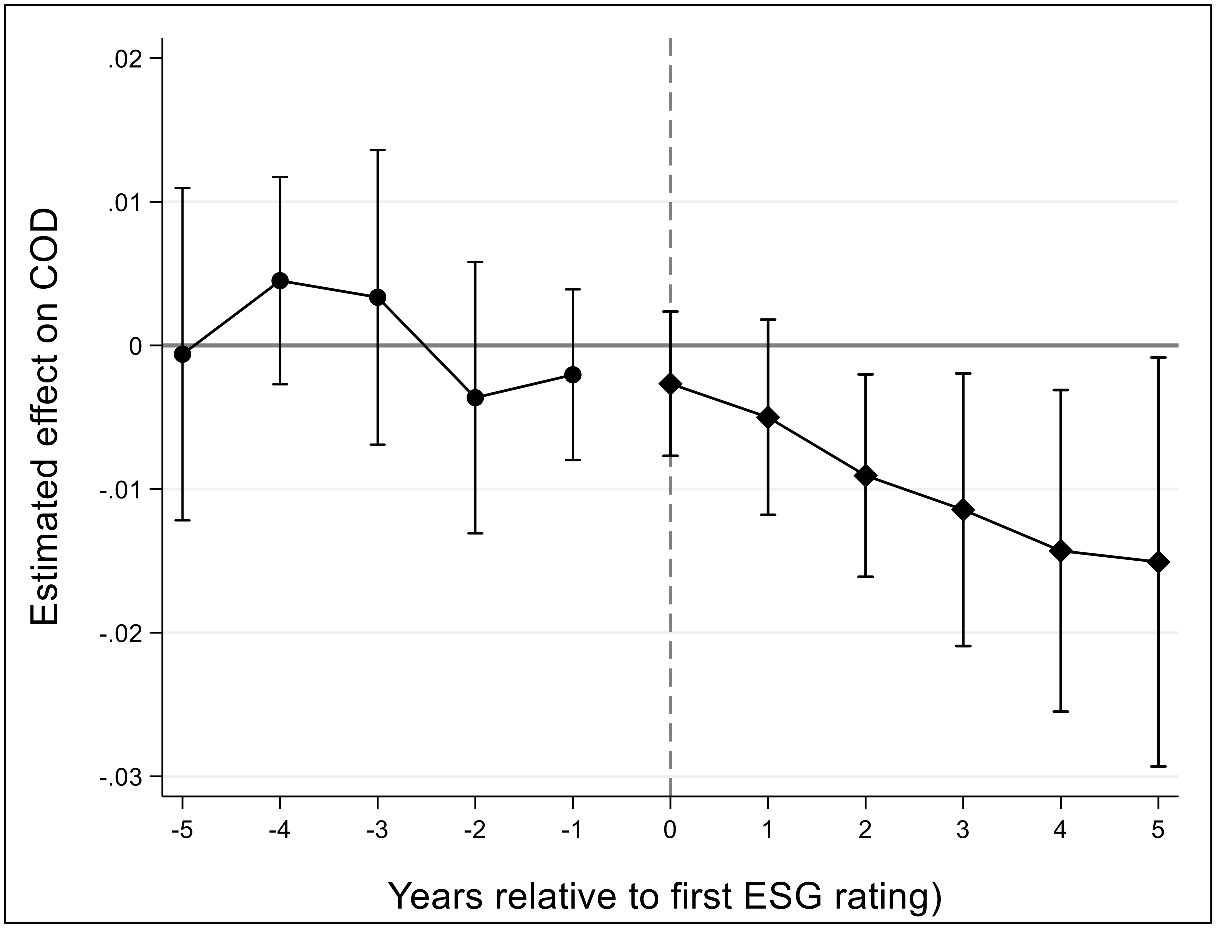
Panel E – Firm Size: Large vs Small (Log Assets)

	Post-treated ATT	Pre-treated ATT	Post 0–2 years	Post 3–5 years	Post 6-8 years	Obs
Large Firms	-0.015**	0.006***	-0.008*	-0.020**	-0.043***	520
	(0.006)	(0.002)	(0.004)	(0.009)	(0.011)	
Small Firms	-0.013***	0.001	-0.009**	-0.017**	-0.043***	385
	(0.005)	(0.003)	(0.004)	(0.007)	(0.007)	

This table reports heterogeneous treatment effects of first-time ESG rating initiation on the cost of debt (COD), estimated using the Callaway and Sant'Anna (2021) difference-in-differences framework on the propensity-score matched sample of Italian publicly listed non-financial firms over 2013–2023. The dependent variable is COD, defined as total interest expense divided by total interest-bearing debt. Each panel presents results for a subsample split by a pre-treatment characteristic: financial constraints measured by the SA index (Panel A), leverage (Panel B), asset tangibility (Panel C), industry-level carbon intensity (green vs. brown) (Panel D), and firm size based on log assets (Panel E). For each group, we report the overall post-treatment average treatment effect on the treated (ATT), the mean pre-treatment ATT (Pre-average), and horizon-specific ATTs for 0–2, 3–5, and 6–8 years after the first ESG rating. Estimates are obtained using the doubly robust inverse probability weighted estimator; standard errors are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

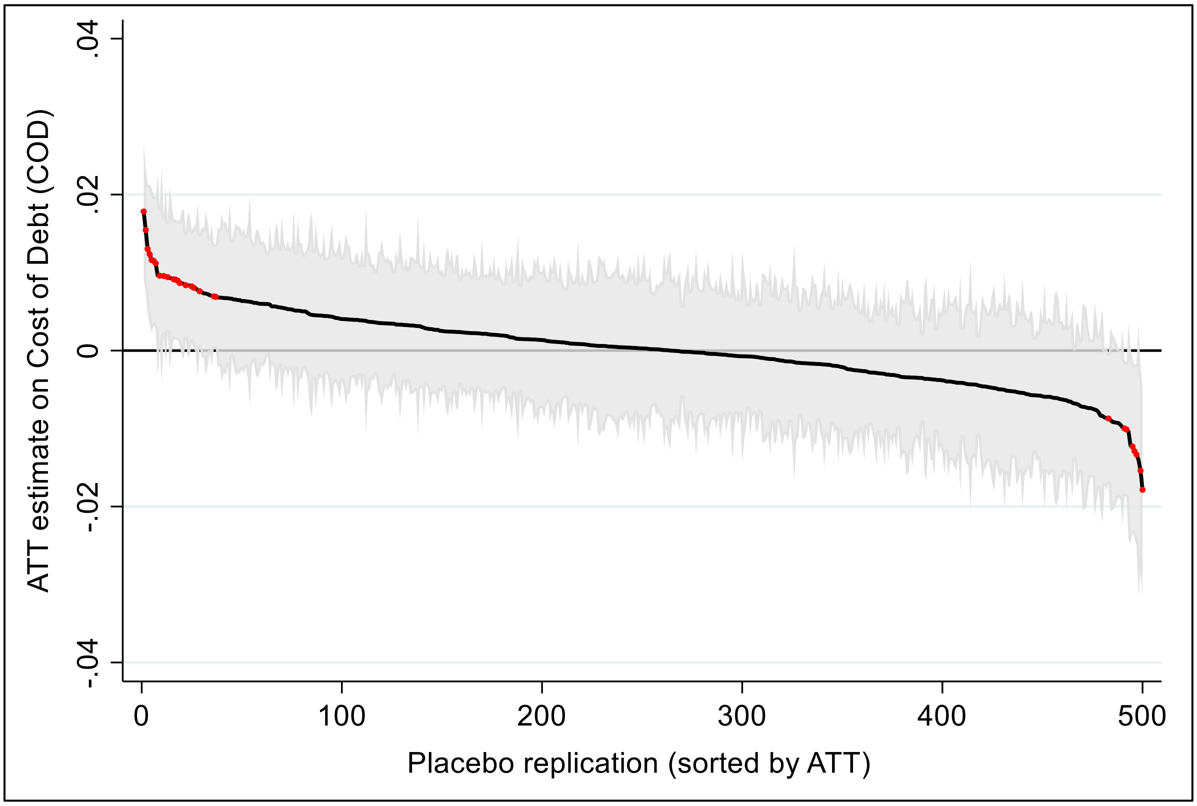
Figures

Figure 1. Dynamic Effects of ESG Rating Initiation on the Cost of Debt



This figure plots event-time estimates from the Callaway and Sant'Anna (2021) difference-in-differences estimator of the average treatment effect on the treated (ATT) of obtaining an ESG rating on firms' cost of debt. The y-axis reports the estimated effect on the cost of debt in percentage points, and the x-axis shows years relative to the first ESG rating (year 0). Each point represents the estimated ATT in a given event year; circular markers denote pre-treatment years and diamond markers denote post-treatment years. Vertical bars indicate 95% confidence intervals based on standard errors clustered at the firm level.

Figure 2. Placebo distribution of ATT estimates



This figure plots the distribution of placebo estimates of the average treatment effect on the treated (ATT) of obtaining an ESG rating on firms' cost of debt (COD). The sample include firms that never obtain an ESG rating over our sample period and firms that do obtain an ESG rating, but only in the years before their actual first ESG rating (i.e., pre-treatment years). In each of 500 replications, we randomly assign a pseudo first ESG-rating year to roughly half of the never-treated firms within their feasible adoption window, while the remaining firm-year observations are kept as controls. For each replication, we estimate the overall ATT using the Callaway and Sant'Anna (2021) multi-period DiD estimator on the matched sample and sort the 500 placebo ATTs from largest to smallest along the horizontal axis. The solid blck line shows the placebo ATT point estimates, the shaded area depicts their 95% confidence intervals, and red dots indicate placebo ATTs that are statistically different from zero at the 5% level. The horizontal dashed line marks the zero effect.

Appendices

Appendix A.1. Sample selection criteria/Sample filtration

Step		Firms removed	Firms remaining	Firm-years removed	Firm-years remaining
0	Starting data downloaded from AIDA	–	**520**	–	**5,200**
1	Drop delisted before 2014	44	476	440	4,760
2	Drop financials (NACE 64–66)	59	417	590	4,170
3	Drop problematic listings	7	410	70	4,100
4	Drop firms rated at baseline	29	381	290	3,810
5	Remove pre-listing filler rows	0	381	99	3,711
6	Missing key variables	8	373	1,203	2,508

Appendix A.2. Definition of Variables

Notation	Variable name	Description	Source
TREATED	ESG-rated firm (indicator)	Equals 1 for firms that ever receive an ESG rating during 2013–2023; 0 otherwise.	LSEG
FIRSTESGYEAR	First ESG rating year	Calendar year in which firm *i* first receives an ESG rating from LSEG	LSEG
ESGPOST	Post-ESG (indicator)	Equals 1 for all years where t ≥ *FIRSTESGYEAR* for treated firms; 0 before and for never-treated firms.	LSEG
COD	Cost of debt	Total interest expense divided by total interest-bearing debt.	AIDA
AT	Total Assets	Total assets of the firm in thousands	AIDA
LN_ASSET	Firm size (log assets)	Natural logarithm of total assets	AIDA
LN_SALES	Firm size (log sales)	Natural logarithm of net sales/revenues (used in descriptives and robustness).	AIDA
ROA	Profitability	Net income divided by total assets	AIDA
AGE	Firm age (years)	Years since legal incorporation of the firm	AIDA
LN_AGE	Log firm age	Natural logarithm of *AGE*.	AIDA
LEV	Leverage	Total liabilities to total assets	AIDA
TANG	Tangibility	Net property, plants and equipments divided by total assets	AIDA
SA	SA index (or Hadlock-Pierce)	Computed using the method provided by Hadlock and Pierce (2010)	AIDA

Appendix A.3. Sample distribution by year and industry

Panel A: Sample distribution by year

Year	No of Firms	Percent	Cum.
2014	211	8.41	8.41
2015	218	8.69	17.11
2016	215	8.57	25.68
2017	227	9.05	34.73
2018	238	9.49	44.22
2019	254	10.13	54.35
2020	275	10.96	65.31
2021	294	11.72	77.03
2022	297	11.84	88.88
2023	279	11.12	100
Total	2,508	100	

Panel B: Sample distribution by industry

NACE 1-digit	Freq.	Percent	Cum.
1	184	7.34	7.34
2	662	26.4	33.73
3	189	7.54	41.27
4	347	13.84	55.1
5	169	6.74	61.84
6	330	13.16	75
7	538	21.45	96.45
8	45	1.79	98.25
9	44	1.75	100
Total	2,508	100	

Appendix A.4: Event-time estimates from staggered DiD of first ESG rating on outcome variables- Parallel-trends diagnostics

Panel A: Event-time (leads/lags) estimates from Sun and Abraham (2021)

	ATT
t = -5	0.005
	(0.005)
t = -4	0.000
	(0.005)
t = -3	0.004
	(0.005)
t = -2	0.002
	(0.003)
t = 0	-0.003
	(0.003)
t = +1	-0.008**
	(0.004)
t = +2	-0.012***
	(0.004)
t = +3	-0.013***
	(0.005)
t = +4	-0.014**
	(0.006)
t = + 5	-0.018***
	(0.007)
Constant	0.042***
	(0.001)
Observations	1028
R-squared	0.7312
Firm, Year & Ind FE	YES

Panel B: Joint pre-trend test

	COD
Chi2 (4)	2.52
P-value	0.6418

Panel A reports event-time estimates from a staggered difference-in-differences design where the dependent variable is the cost of debt (*COD*). Coefficients correspond to indicators for $t = -5$, $t = -4$, $t = -3$, $t = -2$ (pre-treatment) and $t = 0$, $t = +1$, $t = +2$, $t = +3$, $t = +4$, $t = +5$ (post-treatment), with $t = -1$ omitted to avoid multicollinearity, ensure model identification and so that all effects are measured relative to the last pre-treatment year (by folloiwng Sun & Abraham (2021), Hansen, Pererz and Shapiro (2023). Column 1 reports event-study estimates from a two-way fixed-effects specification, and Column 2 presents interaction-weighted event-study estimates following Sun and Abraham (2021, *Journal of Econometrics*). The treatment cohort is defined by each firm's first ESG-rating year, and never-treated firms are retained as controls. The estimation sample is restricted to the one-to-one PSM matched sample and all variables used in the estimation are defined in Appendix A.2. All regressions include firm, year, and industry (based on NACE 1-digit) fixed effects, and robust standard errors clustered at the firm level are reported in parentheses. Panel B assesses the parallel trends assumption. Column 1 reports the F-test of the joint null that the pre-treatment coefficients at $t = -5$, $t = -4$, $t = -3$, and $t = -2$ equal zero for the TWFE specification, while Column 2 reports the corresponding Wald test (shown as a chi-squared statistic) for the Sun–Abraham specification that the coefficients for $t = -5$, $t = -4$, $t = -3$, and $t = -2$ are jointly zero. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.