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Impacts of Japan's Green Bond Guidelines 2020 on ESG bond issuers: A quasi-experimental study using PSM-DID*

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Abstract

This study investigates the impact of Japan's Green Bond Guidelines 2020 on the financial and environmental performance of firms issuing environmental, social, and governance (ESG) bonds. Using a quasi-experimental approach combining propensity score matching (PSM) and difference-in-differences (DID) methodologies, the analysis covers 795 listed Japanese firms from 2016 to 2024. Financial outcomes reveal mixed effects: firms that issued ESG bonds reduce return on assets (ROA) but increase return on equity (ROE), reflecting that revenue growth from ESG bond investment projects lags behind asset growth. Regarding environmental performance, Scope 1 and combined Scope 1 and 2 emissions exhibit significant increases, with Scope 2 and Scope 3 emissions showing no significant changes, indicating a disconnect between ESG bond issuance and actual emission reduction. ESG bonds used for refinancing exhibit negligible impacts on financial and environmental outcomes, whereas those financing new projects yield amplified financial effects. These findings identify challenges, including greenwashing risks and a lack of environmental additionality, wherein ESG bonds that refinance existing projects fail to improve environmental performance. These insights highlight the need for strengthening regulatory frameworks and policies encouraging the development of new ESG programs to enhance transparency, reporting standards, and meaningful environmental contributions.

JEL Classification: C23, Q56, Q58

Keywords: ESG bonds, Financial performance, Environmental additionality, Greenwashing, Sustainable finance

1. Introduction

Green bonds have emerged as pivotal instruments in sustainable finance, facilitating environmental, social, and governance (ESG) practices and promoting responsible business conduct (Flammer, 2020). Allen and Yago (2011) argued that green bonds based on market-based mechanisms and financial innovations can internalize

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environmental costs into the economic decision-making processes of market participants. Previous studies have explored green bonds primarily in terms of bond premiums (Baker et al., 2018; Gianfrate and Peri, 2019; Nanayakkara and Colombage, 2019; Wang et al., 2020; Zerbib, 2019) and stock price responses (Aruga, 2024; Roslen et al., 2017; Baulkaran, 2019; Flammer, 2020; Glavas, 2020; Jakubik and Uguz, 2021). However, limited research has been directed toward exploring long-term financial and environmental performance.

ESG bonds represent a more comprehensive and emerging but rarely studied sustainable financial instrument, including green bonds, sustainability bonds, social bonds, and other specialized bonds. Issued to address specific ESG challenges, ESG bonds finance projects aimed at objectives such as climate mitigation, educational enhancement, and social welfare improvement (Japan Exchange Group, 2023). By channeling capital into sustainable development, ESG bonds serve as key mechanisms for promoting sustainable development and responsible business practices across diverse sectors.

The Ministry of the Environment of Japan publicized the "Green Bond Guidelines 2020" to promote the development of ESG bonds in 2020. The guidelines emphasize assessing and, where feasible, quantifying the environmental and social benefits generated by sustainable financial instruments. Following the publication of these guidelines, the issuance of diverse ESG bonds in Japan surged, with new green bond issuance reaching JPY 398.5 billion in 2020. Sustainability bond issuances increased to JPY 346.1 billion in 2020, compared to just JPY 25 billion in 2019.

Due to information asymmetry, external markets often lack comprehensive information, making it challenging to assess the authenticity and effectiveness of a firm's ESG practices. This information gap allows firms the opportunity to engage in strategic greenwashing (Benlemlih et al., 2022; Fatica and Panzica, 2021; Flammer, 2020; Yeow and Ng, 2021). Bond issuers may claim that the bonds are "green," without genuinely committing to environmental sustainability projects, which can lead to an overly positive reaction in stock prices. Therefore, a thorough evaluation of the long-term financial and environmental performance of firms issuing ESG bonds is essential to address greenwashing concerns and to validate the effectiveness of the Green Bond Guidelines 2020.

Despite this growth, significant gaps remain in understanding the long-term impacts of ESG bonds on financial and environmental outcomes. This study addresses key research questions: whether the guidelines incentivize ESG practices and enhance financial performance within firms. Using data on 795 listed Japanese firms, this analysis applies propensity score matching (PSM) developed by Rosenbaum and Rubin (1983) and a difference-in-differences (DID) approach to examine ESG bonds issued by these firms between January 2016 and January 2024. This study includes manually collected carbon emissions data—encompassing Scope 1, Scope 2, combined Scope 1 and 2 emissions, and Scope 3 emissions—to assess environmental performance. Returns on assets (ROA) and returns on equity (ROE) serve as indicators of long-term financial performance. This comprehensive approach provides a more detailed assessment than previous studies.

The contributions of this study are threefold. First, it addresses the research gap on the impact of ESG bonds in Japan, thereby expanding and enriching the literature on green bonds and sustainable finance. Second, it enhances understanding of the effectiveness of green bond policies at the firm level by comparing environmental and financial performance outcomes of ESG bond issuers against a comparable control group. Third, it provides the first study on the impact of the Green Bond Guidelines 2020 on ESG bond issuers, shedding light on whether the related policy guidelines incentivize investors' ESG preferences and provide insights into their effectiveness in driving sustainability.

2. Literature review and hypothesis development

The Green Bond Guidelines 2020 incorporate ESG factors across a broad spectrum of financial market participants, including issuers, borrowers, investors, financial institutions, and intermediaries. It strengthens the foundation, improves the quality, and expands the financing channels for sustainable finance in Japan. The guidelines promote rapid growth in issuers and diversified ESG bonds. However, the long-term financial impact of ESG bonds remains less explored. Zhou and Cui (2019) examined green bond issuance among Chinese listed firms, revealing positive effects on corporate profitability, operational performance, innovation, and corporate social responsibility. Globally, Flammer (2020) found the positive impact of green bonds on long-term financial performance. However, Yeow and Ng (2021) found no significant financial effect associated with green bonds.

The existing literature on the impact of ESG guidelines on corporate financial performance (CFP) intersects significantly with research on the effects of ESG and socially responsible investment (SRI)-related policies on CFP. Numerous studies suggest a positive relationship between ESG practices and financial outcomes. Quinche-Martín and Cabrera-Narváez (2020) highlighted that the reputational benefits derived from environmental innovation and CSR performance can enhance firms' market value and operational efficiency, thereby improving financial performance. Similarly, Przychodzen and Przychodzen (2015) found that firms engaged in eco-innovation and sustainability exhibit higher ROA and ROE. The green bonds advocated by the Green Bond Guidelines 2020 represent a key financial innovation, broadening access to capital and diversifying financing sources. Furthermore, the implementation of stricter standards and regulations (Albareda et al., 2007) can enhance the quality of financial products, ensuring that environmental benefits are realized alongside economic gains. For investors, this not only diversifies their portfolios and increases the range of available financial products but also enhances their ESG awareness and fosters sustainable financial practices driven by altruistic motivations (Hartzmark and Sussman, 2017; Riedl and Smeets, 2017).

Regarding the relationship between ESG and CFP, Friede et al. (2015) conducted large-scale meta-analyses and vote-count studies, revealing that approximately 63% of meta-analyses and 47% of vote-count studies report a non-negative impact. They also found that fewer than 10% indicates a negative association. Many studies support the positive effect of CSR performance on CFP (Ferrell et al., 2016; Flammer, 2015; Orlitzky, 2001; Tsai and Wu, 2022). Additionally, Bhaskaran et al. (2020), Fatemi et al. (2018), Li et al. (2018), and Yoon et al. (2018) found that ESG practices, ratings, and reporting are positively correlated with firm value.

However, some studies suggest different results. ESG bond investment serves as an emerging and vital component of SRI. Research on portfolio correlations proves a neutral SRI-CFP relationship for both institutional and private investors. This aligns with the neoclassical view of capital markets (Fama, 1970; Friedman, 1970; Fama, 1991). Schröder (2014) contended that SRI does not differ significantly from the risk-adjusted performance of conventional investments. Weston and Nnadi (2021) observed that exchange-traded funds (ETFs) adhering to ESG guidelines do not outperform traditional ETFs in market value. Revelli and Viviani (2014) also observed no clear advantage in CSR-oriented portfolios compared to traditional portfolios in financial performance. Conversely, Gavin et al. (2022) reported a negative association between ESG ratings and financial success. Chen et al. (2023) also found that ESG performance is linked to lower enhanced stock performance. Based on the literature, the following hypothesis is proposed:

Hypothesis 1: The introduction of the Green Bond Guidelines 2020 positively impacts the long-term financial performance of firms that issue ESG bonds.

The Green Bond Guidelines 2020 introduced by the Ministry of the Environment of Japan encourage the adoption of various ESG financial products, including green bonds, sustainability bonds, green loans, and sustainability-linked loans. Among these, green bonds are considered the most significant tool for financing projects aimed at achieving sustainability objectives (Ordonez-Borrallo et al., 2024). Following the guidelines, despite the proliferation of different ESG bonds, green bonds hold a dominant position within ESG bonds. ESG bonds allocate funds toward specific sustainable projects, effectively guiding the flow of capital into environmentally beneficial projects, thereby enhancing overall green performance.

However, concerns about greenwashing—a practice where firms falsely present their investments as environmentally friendly to attract eco-conscious investors while actually investing in non-environmentally beneficial projects—remain prevalent (Ministry of the Environment of Japan, 2020; Environmental Finance, 2023). Greenwashing undermines the integrity of ESG bonds and can dilute their environmental impact. The green bond market operates under a system of private governance (Fatica and Panzica, 2021). While the Green Bond Guidelines 2020 outline criteria for fund usage, management, and review, they are not legally binding. This voluntary nature of the guidelines raises concerns about the effectiveness of ESG bonds in delivering genuine environmental benefits if greenwashing is widespread. Therefore, it is crucial to examine whether the Green Bond Guidelines 2020 can substantially influence the environmental performance of firms issuing ESG bonds.

Research on green bonds' role in promoting corporate environmental performance (CEP) presents mixed findings. Ordonez-Borrallo et al. (2024) argued that green bonds can enhance corporate managers' focus on environmental performance and increase awareness of sustainability. Flammer (2020) used a market model and DID method, reporting that green bonds can lead to significant reductions in carbon emissions. Using the same approach, Yeow and Ng (2021) found that green bonds, when subject to third-party certification, positively impact environmental performance. Similarly, Benlemlih et al. (2022) reported that green bonds significantly enhance overall environmental performance, although the benefits may take a year or more to materialize.

Fatica and Panzica (2021) demonstrated that green bonds reduce total and Scope 1 emissions from non-financial firms, with greater reductions observed when refinancing bonds are excluded. This finding highlights the potential for green bonds to deliver additional environmental benefits, referred to as "additionality." In contrast, Bongaerts and Schoenmaker (2020) argued that green bonds fail to generate additionality, as they predominantly refinance existing green projects rather than fund new ones. Consequently, these bonds do not necessarily improve environmental performance. Furthermore, the decentralized issuance of green bonds reduces their liquidity, increasing financing costs and limiting the incentive for firms to pursue new environmental initiatives. Supporting this view, Wei et al. (2022) found that while green bond issuance can alleviate financial constraints, it does not lead to improved environmental performance. They emphasized that national and industry-level environmental regulations positively influence the relationship between green bond issuance and carbon performance. Given these considerations, the following hypothesis is proposed:

Hypothesis 2: The introduction of the Green Bond Guidelines 2020 positively impacts the environmental performance of firms that issue ESG bonds.

3. Research methodology

3.1 Quasi-experimental examination using PSM-DID methods

This study uses the DID model with PSM methods to explore the impacts of the Green Bond Guidelines 2020 on corporate financial and environmental performance of ESG bond issuers in Japan. The DID method designates listed firms that have issued ESG bonds as the treatment group, while other listed firms that have not issued ESG bonds serve as the control group. The study then calculates the difference in long-term financial performance between these groups before and after the implementation of the Green Bond Guidelines 2020.

The DID method does not require completely randomized assignment between treatment and control groups but instead relies on the parallel trend assumption. This assumption ensures that, in the absence of treatment, both groups would have exhibited similar trends over time, thus minimizing bias. Firms that have issued ESG bonds may have been selected based on specific factors, such as particular industry characteristics, firm size, and financial stability. This study addresses the endogeneity problem related to selection bias by employing the PSM technique originally developed by Rosenbaum and Rubin (1983) prior to applying the DID method. Following Flammer's (2020) application on financial performance and Fu et al. (2021)'s application on carbon emissions, this study estimates the policy's impact that it is uncontaminated by selection bias.

To establish a control group, this study matches firms that issued ESG bonds with firms that did not, based on criteria such as industry, age, financial characteristics, and CSR ratings. Creating comparable treatment and control groups enhances its robustness. This study uses a logit model, as specified in equation (1), to estimate parameters and predict propensity scores.

$$p\left(\boldsymbol{Z}_{i,t}\right) = \Pr\left(\boldsymbol{D}_i = 1 \middle| \boldsymbol{Z}_{i,t}\right) = \frac{1}{1+\exp\left(-\boldsymbol{Z}'_{i,t}\boldsymbol{\beta}\right)} \quad . \tag{1}$$

$\boldsymbol{Z}_{i,t}$ represents matching variables that influence the likelihood of a firm issuing ESG bonds. $\boldsymbol{D}_i$ is the indicator variable that equals 1 if a firm issues ESG bonds and 0 otherwise, and $\boldsymbol{\beta}$ denotes the vector of coefficients. Both radius matching and kernel matching techniques are used to execute PSM.

The PSM estimates the probability that a firm will issue ESG bonds based on observed characteristics (propensity scores) and then matches treated firms with control firms that have similar propensity scores to create balanced sets with comparable covariate distributions (Stuart, 2010). This matching process minimizes significant differences in key variables between the treated and control groups before treatment, improving the validity of causal inferences. While PSM cannot fully eliminate biases from unobserved factors, it effectively reduces selection bias from observed factors (Rosenbaum and Rubin, 1983; Rubin and Thomas, 1992), thereby enhancing the comparability of groups and improving the accuracy of DID estimates (Becker and Ichino, 2002).

3.2 Data sources and variable definitions

The data source on ESG bonds in Japan is the website of the Ministry of the Environment of Japan‡. Financial data pertaining to Japanese listed firms comes from the EDINET and EOL databases, as well as Nikkei Firm Information DIGITAL. CSR ratings are from the TOYOKEIZAI annual CSR research reports. Industry-related data is sourced from the portal site of the official statistics portal of Japan, e-Stat. The manually gathered greenhouse gas (GHG) emissions data is from corporate official websites, ESG databooks, CSR reports, and annual unified reports of listed firms. Table 1 provides a detailed overview of the specific variables, their measurements, units, and sources.

Table 1. Variable specification and measurement

Variable	Indicator	Unit	Source
Total assets (TA)	Market value of total assets	Millions of yen	EOL database
Total liabilities (TL)	Market value of total liabilities	Millions of yen	EOL database
Return on assets (ROA)	Divide net income by total assets and multiply by 100	%	EDINET and EOL databases
Return on equity (ROE)	Divide net income by shareholders' equity and multiply by 100	%	EDINET and EOL databases
Corporate size ($SIZE$)	Logarithmic value of total assets		EOL database
Financial leverage (LEV)	Divide total debt by market value of total assets and multiply by 100	%	EOL database
Cashflow (CF)	Cash and cash equivalents at the end of period	Millions of yen	EOL database
Price earnings ratio (PER)	Market price per share divided by earnings per share		EOL database
Shareholders' equity ratio ($SHARE$)	Divide total shareholders' equity by total assets and multiply by 100	%	EOL database
CSR rating (CSR)	CSR rating		TOYOKEIZAI annual CSR research reports
Corporate age (AGE)	The difference between the current year and the year in which the firm was established	year	Nikkei Firm Information DIGITAL
Industry growth rates ($INDUSGR$)	Percentage change in the industry's added value from one period to the next.	%	e-Stat
Direct emissions ($Scope1$)	Direct GHG emissions from sources that are owned or controlled by the firm	kt-CO_2	Corporate official websites, ESG databooks, CSR reports, annual unified reports
Indirect emissions from energy consumption ($Scope2$)	Indirect GHG emissions through the use of electricity, heat, and steam supplied by other firms	kt-CO_2	Corporate official websites, ESG databooks, CSR reports, annual unified reports
Total of Scope 1 and Scope 2 emissions ($Scope12$)	Data for $Scope12$ were derived either from total emissions disclosed without separate $Scope1$ and $Scope2$ data or by summing individually reported $Scope1$ and $Scope2$	kt-CO_2	Corporate official websites, ESG databooks, CSR reports, annual unified reports
Indirect emissions from the value chain ($Scope3$)	All other indirect GHG emissions that occur in a firm's value chain	kt-CO_2	Corporate official websites, ESG databooks, CSR reports, annual unified reports

‡ Data on ESG bond issuance in Japan were obtained from the Ministry of the Environment's Green Finance Portal. For further details, please see https://greenfinanceportal.env.go.jp/en/bond/issuance_data/issuance_list.html.

3.3 Estimation model

This study utilizes the Japanese government's Green Bond Guidelines 2020 policy as a quasi-natural experiment. Firms that issued ESG bonds are designated as the treatment group, while matched firms that did not issue ESG bonds serve as the control group. This study employs a DID model to assess whether the introduction of the Green Bond Guidelines 2020 can enhance both the financial performance and environmental outcomes of firms issuing ESG bonds. The empirical model is as follows:

$$Outcome\ Variable_{i,t} = \alpha + \gamma_1 ESG_{i,t} + \gamma_2 Post_{i,t} + \gamma_3 ESG \times Post + Firm\ controls_{i,t} + Industry\ controls_{\ i,t} + \lambda_t + \varepsilon_{i,t} \quad . \tag{2}$$

The subscripts i and t represent the firm and year, respectively. $ESG_{i,t}$ is a dummy variable for ESG bonds, where 1 indicates firms that issued ESG bonds and 0 indicates firms that did not. Since the guidelines were introduced on March 10, 2020, part of that fiscal year might be impacted by the policy. Therefore, the post-policy period starts in fiscal year 2020. The variable $Post_{i,t}$ is a dummy variable that takes the value of 1 for t in 2020 and beyond, and 0 for all prior periods. The interaction term $ESG \times Post$ is the DID interaction term. It takes the value of 1 for ESG bond-issuing firms after the introduction of these guidelines. A significant positive coefficient for γ_3 would indicate that the Green Bond Guidelines 2020 have a positive incentive effect on the financial performance of firms that issue ESG bonds. Control variables include firm-level control variables $Firm\ controls_{i,t}$ and industry-level control variables $Industry\ controls_{\ i,t}$. The main firm-level control variables include firm size ($SIZE_{i,t}$), total assets ($TA_{i,t}$), total liabilities ($TL_{i,t}$), financial leverage ($LEV_{i,t}$), cashflow ($CF_{i,t}$), price earnings ratio ($PER_{i,t}$), ownership capital ratio ($SHARE_{i,t}$), CSR ratings ($CSR_{i,t}$), and firm age ($AGE_{i,t}$). Since the industry fixed effects are absorbed by individual fixed effects, the time-invariant characteristics of the industry are already controlled for. Therefore, this model also controls for time-varying industry-specific factors, such as industry growth rates $INDUSGR_{i,t}$. λ_t denotes the time fixed effects.

3.4 Descriptive statistics

Table 2 summarizes 4594 observations from 795 firms, revealing significant variability in financial variables and firm characteristics related to CSR ratings and ESG bond issuance. The mean ROA is 33.96%, with the 50th percentile at 10.8%, showing a wide range of asset profitability. ROE presents a greater mean value of 59.83% and shows a higher standard deviation (SD) of 57.7. These results suggest that firms in the sample are quite profitable relative to shareholders' equity, despite significant variability. Firms are relatively mature, averaging 69.1 years, with notable differences in size, leverage, and cash flows. Industry growth rates vary widely (mean: 9.51%, SD: 34.3), with top 75th percentile values below 8.13%. Scope 3 emissions dominate environmental performance (mean: 9803, SD: 29453), highlighting the value chain's impact. CSR ratings are generally strong, with 49.72% rated AA or higher, but ESG bond issuance is limited to 16.15%.

Table 2. Descriptive statistics

Variable	Mean	SD	Min	Max	p25	p50	p75	N
TA	3.600e+06	2.300e+07	2036	3.900e+08	51429	240000	1.100e+06	4594
TL	3.100e+06	2.200e+07	676	3.700e+08	22927	100000	650000	4594
ROA	33.96	38.01	–27	146	5.400	10.80	62	4594
ROE	59.83	57.70	–374.1	204	9	45	100	4594
SIZE	12.06	1.820	7.620	17.78	10.67	11.94	13.37	3905
LEV	55.36	20.07	13.42	96.77	41.01	54.28	68.69	4594
CF	610000	5.200e+06	1	1.100e+08	4316	19954	79230	4593
PER	71.01	60.41	–9.700	266	21	54.50	109	4590
SHARE	43.31	20.74	–0.300	103	28.90	44.60	58	4594
AGE	69.10	28.70	0	145	56	72	86	4594
INDUSGR	9.51	34.30	–33.97	219.0	0.08	1.05	8.13	4594
*Scope*1	1864	7251	0	88900	6.040	51.68	243.9	1363
*Scope*2	313.5	823.2	0	7400	12.45	53.68	225.5	1374
*Scope*12	1807	6420	0.0900	92600	20.29	96.31	472	1833
*Scope*3	9803	29453	0.210	330000	514.6	2039	5013	940
CSR	Frequency		Percent					
AAA	571		12.43					
AA+	32		0.70					
AA	1681		36.59					
AA-	253		5.51					
A+	306		6.66					
A	975		21.22					
A-	391		8.51					
B	166		3.61					
BBB	54		1.18					
BBB+	105		2.29					
BBB-	16		0.35					
C	44		0.96					
Total	4594		100.00					
ESG	Frequency		Percent					
0	3852		83.85					
1	742		16.15					
Total	4594		100.00					

Notes: All variables, except for the dummy variable *ESG*, have been winsorized at the 1st and 99th percentiles. The descriptive statistics include the number of observations, mean, maximum, minimum, standard deviation, and the 25th, 50th, and 75th percentiles for each variable.

4. Results

4.1 Impacts of Green Bond Guidelines 2020 on corporate financial performance

This section reports the estimated impacts of the Green Bond Guidelines 2020 on firms' long-term financial performance, specifically measured by ROA and ROE. ROA and ROE are widely utilized financial metrics for assessing a firm's long-term financial performance (Murphy et al., 1996; Ordonez-Borrallo et al., 2024).

4.1.1 The radius matching PSM results

To mitigate selection bias, this study uses the radius matching method to apply PSM. The matching variables are selected based on their influence on the probability of a firm issuing ESG bonds. A total of ten variables are included: $SIZE$, LEV, TA, TL, CF, CSR, PER, $SHARE$, AGE, and $INDUSGR$.

Figure 1 presents the distribution of propensity scores for the treatment and control groups. The results indicate that 155 listed firms in the control group do not satisfy the common support assumption. This means that they have an exceptionally high or low probability of issuing ESG bonds. Consequently, these firms are excluded from further analysis. The final sample comprises 689 firms that meet the common support assumption, with 108 listed firms in the treatment group and 581 listed firms in the control group.

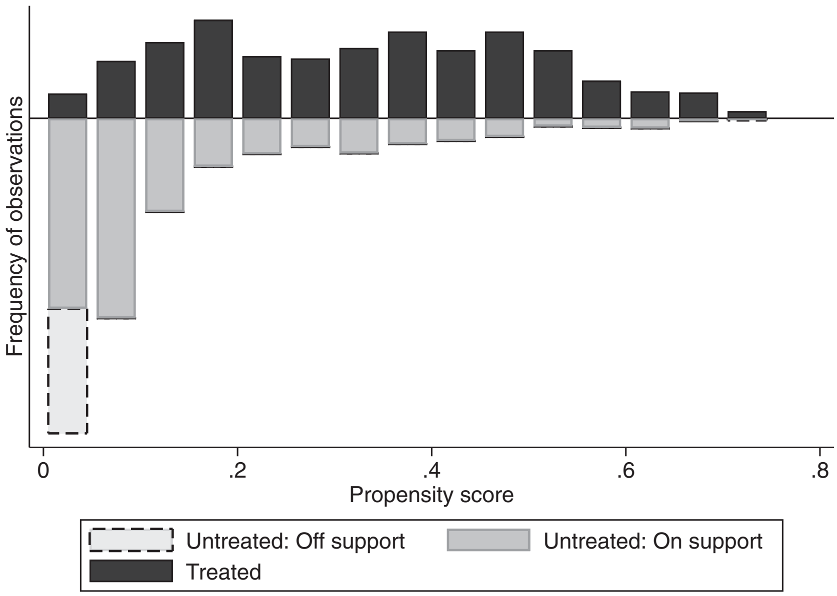
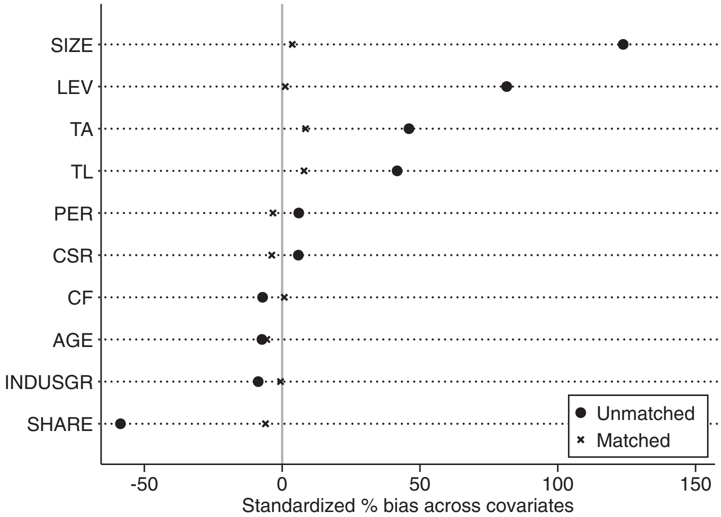


Figure 1. Propensity score distribution using radius matching

Figure 2 presents an intuitive comparison of the standardized percentage bias across various variables before and after PSM. Several variables, particularly $SIZE$, LEV, TA, and TL, exhibit substantial bias before matching. However, after applying PSM, the bias was significantly reduced. For instance, the bias in firm size was nearly eliminated, reduced to approximately 0%. We can observe similar reductions for LEV, TA, and TL. Appendix 1 and Appendix 2 show the specific balance test results of variables before and after radius matching for ROA and ROE, respectively. Overall, the bias across all variables was effectively minimized, bringing them close to zero. This visual comparison reinforces the conclusion that PSM has greatly enhanced the balance between the treatment and control groups.



Notes: The black dots represent the standardized percentage bias for each variable before matching (unmatched). The crosses (×) indicate the standardized percentage bias after matching (matched).

Figure 2. Standardized percentage bias before and after radius matching in PSM (financial impacts)

4.1.2 Parallel trend test

Figure 3 shows the parallel trend test results for ROA and ROE. This test is a crucial assumption in DID analysis, assessing whether the treatment group (firms that have issued ESG bonds) and the control group (firms that have not issued ESG bonds) exhibited similar trends in the outcome variable before the implementation

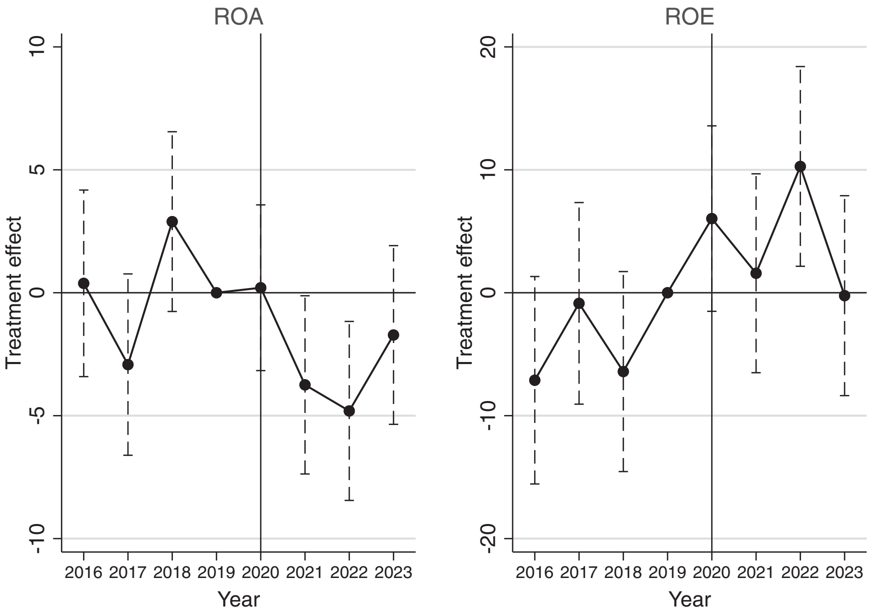


Figure 3. Parallel trend test results for financial impacts (radius PSM)

of the Green Bond Guidelines in 2020. The pre-intervention period (2016–2019) demonstrates no significant differences between the two groups, confirming that the parallel trend assumption is met. Post-2020, the treatment effect for ROA becomes significantly negative in 2021 and 2022, while the treatment effect for ROE also becomes significantly positive in 2022.

4.1.3 Baseline regression results for financial impacts

Table 3 reports the regression results for ROA and ROE with firm and time fixed effects. Column (1) suggests

Table 3. Regression analysis results for financial impacts

Variables	(1) *ROA*	(2) *ROE*
ESG	–28.964 ***	45.547 **
	(–2.84)	(1.99)
Post	–6.341	–1.843
	(–1.51)	(–0.20)
ESG × *Post*	–2.399 **	7.842 ***
	(–2.12)	(3.09)
TA	6.36e–07	–5.82e–07
	(1.39)	(–0.57)
TL	–4.27e–07	4.23e–07
	(–1.11)	(0.49)
SIZE	9.447 ***	2.791
	(4.25)	(0.56)
LEV	–0.497 ***	–0.543 ***
	(–7.32)	(–3.55)
ROE	0.133 ***	0.669 ***
	(17.30)	(17.30)
CF	0.000	–0.001
	(1.09)	(–1.53)
CSR	–0.282	0.199
	(–1.12)	(0.35)
PER	0.007 ***	0.046 ***
	(2.73)	(7.73)
SHARE	0.006 *	–0.002
	(1.88)	(–0.32)
AGE	–0.014	–0.386
	(–0.02)	(–0.30)
INDUSGR	0.017 **	0.051 ***
	(2.00)	(2.63)
Constant	–63.355	46.465
	(–1.35)	(0.44)
Observations	3766	3766
R-squared	0.172	0.149
Firm FE	YES	YES
Year FE	YES	YES
Number of firms	689	689

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. To maintain conciseness, the coefficients for year dummy variables are not reported in this table.

that the coefficient for the interaction term $ESG \times Post$ is negative and significant at –2.399 at the 5% level. This indicates that firms that have issued ESG bonds experience a reduction in ROA of 2.399 points, approximately a 7.1% decline from the mean ROA, after the issuance of the Green Bond Guidelines 2020, compared to firms that have not issued ESG bonds. Column (2) reveals a positive coefficient for $ESG \times Post$, with a value of 7.842, significant at the 1% level. This suggests that firms issuing ESG bonds experience a roughly 17.4% increase from the median ROE post-treatment, compared to firms that have not issued ESG bonds.

Control variables provide key insights into financial performance. As shown in Column (1), larger firms and those in faster-growing industries tend to achieve better ROA performance. In addition, higher ROE, PER, and shareholders' equity ratio are positively associated with improved ROA. Conversely, higher leverage is linked to poorer ROA performance, indicating that increased debt levels adversely affect profitability. Column (2) suggests that higher industry growth rates, ROA, and PER positively influence ROE, whereas increased leverage negatively impacts ROE performance. This reinforces the notion that increased debt levels may negatively affect a firm's profitability.

4.2 Impacts of Green Bond Guidelines 2020 on corporate environmental performance

This section investigates the impact of the Green Bond Guidelines 2020 on CEP, specifically focusing on carbon emissions as the primary indicator. To provide a comprehensive view of the effects of carbon emissions, this study assesses both direct and indirect carbon impacts based on the Greenhouse Gas Protocol, the most widely adopted GHG accounting standard globally. Scope 1 emissions ($Scope1$) represent direct GHG emissions from sources owned or controlled by the firm. Scope 2 emissions ($Scope2$) reflect the GHG emissions associated with the consumption of purchased electricity. $Scope12$ denotes the total Scope 1 and Scope 2 emissions. Scope 3 emissions ($Scope3$) encompass all other indirect GHG emissions occurring within the firm's value chain but originating from sources not owned or controlled by the firm.

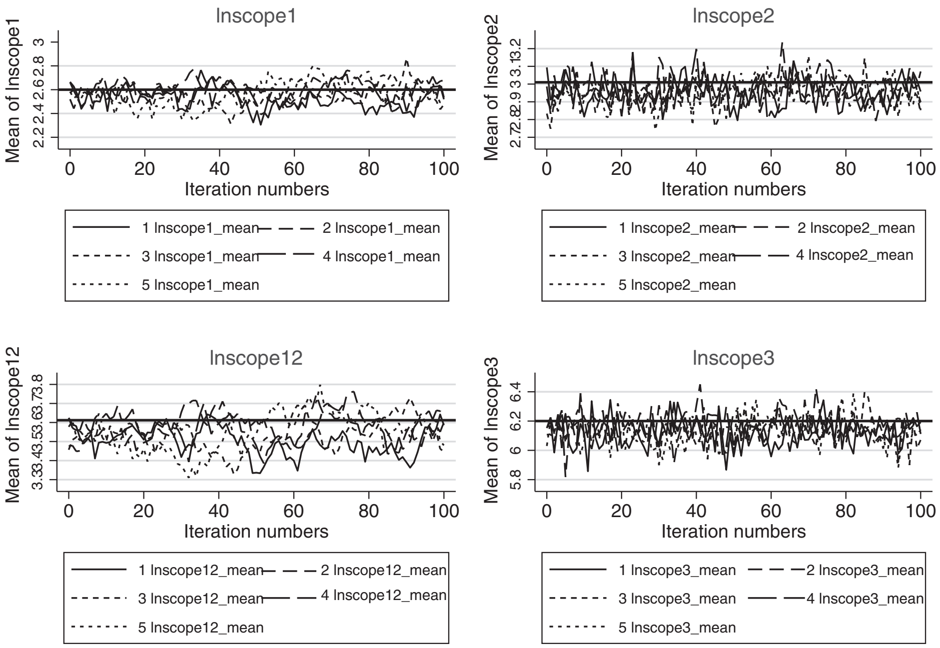
4.2.1 Addressing missing data with Multiple Imputation by Chained Equations

Given the challenges of incomplete carbon emissions data and the short timeframe for the harmonization of accounting standards, there is substantial missing data in the manually collected data for $Scope1$, $Scope2$, $Scope12$, and $Scope3$. To address these gaps, this study employs a multiple imputation method that effectively minimizes the issues associated with incomplete data and offers significant advantages over methods such as the deletion of missing values or provisional value estimation (Kofman and Sharpe, 2003). In addition, before conducting multiple imputation, the data for $Scope1$, $Scope2$, $Scope12$, and $Scope3$ were log-transformed to reduce the effects of heteroscedasticity. Their logarithmic values are denoted as $lnscope1$, $lnscope2$, $lnscope12$, and $lnscope3$, respectively.

This study employs a flexible multiple imputation method, Multiple Imputation by Chained Equations (MICE). This method assumes that missing data are missing at random, meaning the probability of missingness depends solely on observed data (Graham, 2009). The MICE process begins with a simple initial imputation, such as mean replacement, as a placeholder for each missing value (Azur et al., 2011). Each variable with missing data is then regressed on other variables in the dataset to generate predictions, which replace the initial placeholders. This iterative process continues for all variables until the model converges, achieving stability for imputation (Van Buuren, 2007). By iteratively applying regression models for each variable, MICE can flexibly handle complex data structures with suitable regression techniques (Raghunathan et al., 2000; Van Buuren, 2007). This analysis employs linear regression models for continuous variables such as $lnscope1$, $lnscope2$, $Scope12$, and $lnscope3$ to ensure accurate predictions aligned with their characteristics.

MICE offers significant advantages over single imputation methods by creating multiple imputed datasets, which better capture the uncertainty of missing data and produce more accurate standard errors (Schafer and Graham, 2002). Results from these datasets are combined using Rubin's (1987) and Schenker and Taylor's (1996) standard rules to derive final estimates. Moreover, MICE's adaptability and flexibility make it effective for complex and large-scale datasets (Azur et al., 2011), thereby enhancing the robustness of data analysis (Collins et al., 2001).

This study applies the convergence properties of MICE by performing 100 iterations with a specified random number of seed to ensure reproducibility. This approach aims to observe the aggregation trends of carbon emission estimates over these iterations. Figure 4 illustrates the mean values of five imputations for each variable ($lnscope1$, $lnscope2$, $Scope12$, and $lnscope3$) over the iterations. The horizontal black lines



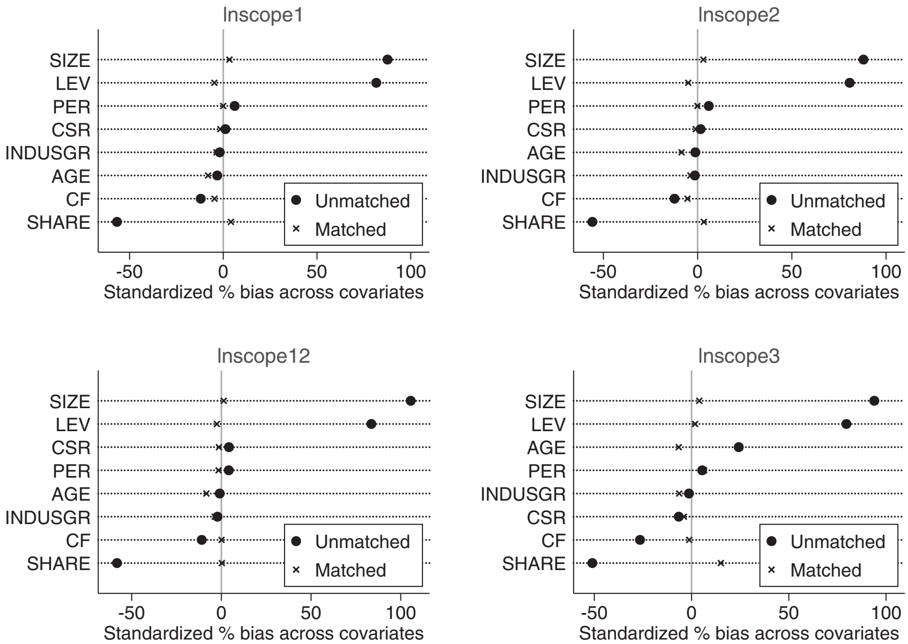
Notes:1 $lnscope1\_mean$, 2 $lnscope1\_mean$, 3 $lnscope1\_mean$, 4 $lnscope1\_mean$ and 5 $lnscope1\_mean$ denote the mean values of the five imputations for $lnscope1$. 1 $lnscope2\_mean$, 2 $lnscope2\_mean$, 3 $lnscope2\_mean$, 4 $lnscope2\_mean$ and 5 $lnscope2\_mean$ denote the mean values of the five imputations for $lnscope2$. 1 $lnscope12\_mean$, 2 $lnscope12\_mean$, 3 $lnscope12\_mean$, 4 $lnscope12\_mean$ and 5 $lnscope12\_mean$ denote the mean values of the five imputations for $lnscope12$. 1 $lnscope3\_mean$, 2 $lnscope3\_mean$, 3 $lnscope3\_mean$, 4 $lnscope3\_mean$ and 5 $lnscope3\_mean$ denote the mean values of the five imputations for $lnscope3$.

Figure 4. Convergence analysis of imputed carbon emission estimates using MICE

represent the observed mean values for each variable, providing a reference point to evaluate the stability of the imputations. As shown in Figure 4, all five chains exhibit fluctuations around the observed mean estimates of each variable. This consistent oscillation around the mean indicates convergence, suggesting that the MICE algorithm has stabilized across imputations.

4.2.2 The radius matching PSM results

Considering the correlation with carbon emission variables, this study uses eight matching variables for the PSM by excluding TA and TL. As shown in Figure 5, the standardized percentage bias for $lnscope1$, $lnscope2$, $lnscope12$, and $lnscope3$ decreases significantly after radius matching, with all variables achieving a bias reduction below 10%. This indicates a substantial improvement in the balance between the treatment and control groups, ensuring comparability.



Notes: The black dots represent the standardized percentage bias for each variable before matching (unmatched). The crosses (×) indicate the standardized percentage bias after matching (matched).

Figure 5. Standardized percentage bias before and after radius matching in PSM (environmental impacts)

4.2.3 Parallel trend test

Figure 6 presents the results of the parallel trend test conducted using the imputed values of $lnscope1$, $lnscope2$, $lnscope12$, and $lnscope3$ prior to the DID analysis. For all four variables, the treatment effects do not exhibit significant differences from zero before 2020, suggesting that the parallel trend assumption is satisfied. Post-2020 changes reflect possible treatment impacts. $lnscope1$ and $lnscope2$ show modest upward trends in treatment effects, while $lnscope12$ displays a significant increase in 2022. $lnscope3$ maintains stable and insignificant treatment effects.

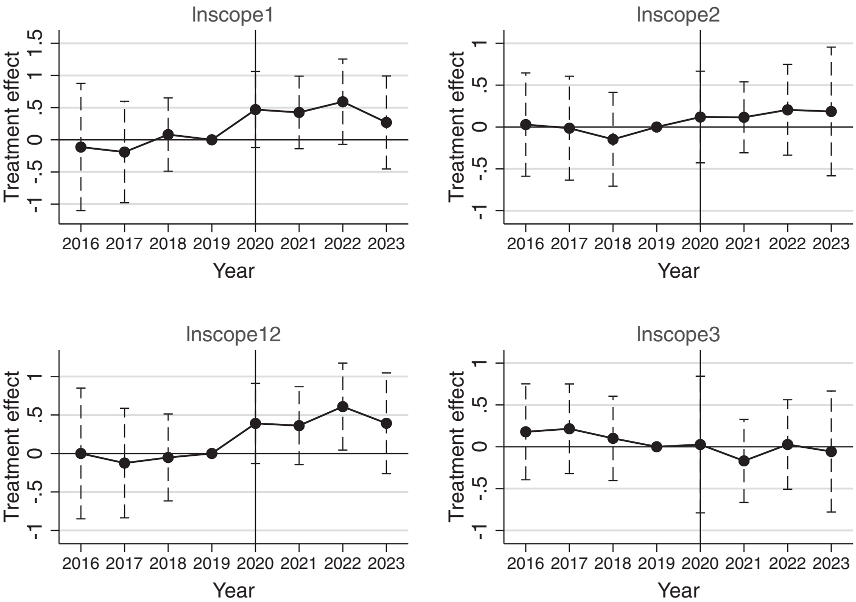


Figure 6. Parallel trend test results for environmental impacts (radius PSM)

4.2.4 Baseline regression results for environmental impacts

Table 4 presents the regression analysis results for various carbon emission scopes using fixed effects models with firm and year controls. The interaction term $ESG \times Post$ shows a statistically significant and positive effect on $lnscope1$ and $lnscope12$, with coefficients of 0.490 (Column (1)), corresponding to approximately a 6.72% increase in mean Scope 1 emissions, and 0.432 (Column (3)), indicating roughly a 5.93% increase in the mean value of combined Scope 1 and Scope 2 emissions. Both results are significant at the 1% level, suggesting that post-intervention firms experienced increased emissions in these categories. However, this treatment effect is not significant for $lnscope2$ and $lnscope3$.

Control variables reveal mixed effects: leverage (LEV) consistently shows a negative and significant impact across all emission types, indicating that more leveraged firms tend to have lower emissions. $SHARE$ positively influences emission reduction, particularly for Scope 1 emissions, while PER suggests firms with higher valuation ratios tend to reduce Scope 1 emissions.

Overall, while the 2020 Green Bond Guidelines may have promoted green bond issuance and ESG investments, they do not lead to a significant reduction in Scope 1 and combined Scope 1 and Scope 2 emissions. They have minimal impact on Scope 2 and Scope 3 emissions. This reflects the limited direct impact of ESG policies on overall environmental performance.

Table 4. Regression analysis results for environmental impacts

Variables	(1) *lnscope*1	(2) *lnscope*2	(3) *lnscope*12	(4) *lnscope*3
ESG	0.333	–0.435	0.262	0.976
	(2.337)	(1.440)	(1.925)	(2.042)
Post	0.668	–0.428	0.236	–0.010
	(0.879)	(0.703)	(0.631)	(0.626)
ESG × *Post*	0.490***	0.187	0.432***	–0.239
	(0.182)	(0.271)	(0.159)	(0.211)
SIZE	0.108	0.353	0.184	0.104
	(0.654)	(0.318)	(0.459)	(0.316)
LEV	–0.056***	–0.037***	–0.044***	–0.038**
	(–0.014)	(0.010)	(0.013)	(0.014)
ROA	0.001	0.003	–0.001	–0.005
	(0.004)	(0.003)	(0.003)	(0.004)
ROE	–0.0001	–0.006***	–0.004*	0.003*
	(0.002)	(0.001)	(0.002)	(0.001)
CF	–0.0001	0.0001**	–0.00005	–0.0001***
	(0.0001)	(0.00004)	(0.0001)	(0.00003)
CSR	0.053	0.035	0.024	0.035
	(0.055)	(0.034)	(0.056)	(0.045)
PER	–0.001**	–0.001	–0.001	–0.001
	(0.001)	(0.001)	(0.001)	(0.001)
SHARE	–0.004***	–0.001*	–0.002***	–0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
AGE	–0.129	–0.020	–0.087	0.005
	(0.114)	(0.092)	(0.090)	(0.087)
INDUSGR	–0.001	0.002**	–0.002	–0.005***
	(0.002)	(0.001)	(0.002)	(0.002)
Constant	14.788	2.920	11.276	7.667
	(12.133)	(7.993)	(8.855)	(7.275)
Observations	4296	4296	4296	4296
R-squared	0.843	0.654	0.814	0.602
Number of firms	795	795	795	795
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: *, ** and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. To maintain conciseness, the coefficients for year dummy variables are not reported in this table.

5. Heterogeneity analysis

5.1 Temporal trends

This section investigates the time-varying impact of these guidelines by constructing new interaction terms, specifically $yr20\times ESG$, $yr21\times ESG$, $yr22\times ESG$, and $yr23\times ESG$, which are created by multiplying dummy variables for each year from 2020 to 2023 with the ESG variable. These interaction terms assess the temporal heterogeneity of the treatment effect.

Table 5 shows the results of temporal heterogeneity analysis for financial performance. For ROA, the coefficients of the interaction term $yr21\times ESG$ and $yr22\times ESG$ are significantly negative at the 5% and 1% levels, suggesting that the guidelines do not immediately impact ROA, but a dampening effect becomes evident from 2021. This highlights a lagged effect on corporate ROA performance for ESG bond-issuing firms. For ROE, both $yr20\times ESG$ and $yr22\times ESG$ show statistically significant positive coefficients at the 5% and 1% levels, respectively.

Table 5. Time trend analysis results for financial impacts

Variables	*ROA*	*ROE*
ESG	–28.999***	46.188**
	(–2.84)	(2.02)
Post	–6.754	–1.081
	(–1.61)	(–0.11)
$yr20\times ESG$	0.145	9.241**
	(0.09)	(2.44)
$yr21\times ESG$	–3.776**	4.951
	(–2.11)	(1.24)
$yr22\times ESG$	–4.846***	13.651***
	(–2.69)	(3.39)
$yr23\times ESG$	–1.747	3.221
	(–0.97)	(0.80)
Constant	–65.250	44.507
	(–1.39)	(0.42)
Observations	3766	3766
R-squared	0.174	0.150
Number of firms	689	689
Firm FE	YES	YES
Year FE	YES	YES

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. To maintain conciseness, the coefficients for control variables and year dummy variables are not reported in this table.

Table 6 presents the temporal heterogeneity effects of the guidelines on $lnscope1$, $lnscope2$, $lnscope12$, and $lnscope3$. The significant positive coefficients of $yr20\times ESG$ and $yr22\times ESG$ for lnscope1 and $lnscope12$ suggest an immediate and sustained increase in Scope 1 and combined Scope 1 and Scope 2 emissions in 2020 and 2022. In contrast, Scope 2 or Scope 3 emissions suggest no significant effects across the years.

Table 6. Time trend analysis results for environmental impacts

Variables	(1) *lnscope*1	(2) *lnscope*2	(3) *lnscope*12	(4) *lnscope*3
ESG	0.349	–0.432	0.276	0.986
	(2.332)	(1.432)	(1.924)	(2.046)
Post	0.695	–0.428	0.250	–0.021
	(0.898)	(0.721)	(0.638)	(0.613)
$yr20 \times ESG$	0.516**	0.150	0.436**	–0.027
	(0.263)	(0.277)	(0.211)	(0.374)
$yr21 \times ESG$	0.476	0.150	0.361	–0.386
	(0.310)	(0.302)	(0.241)	(0.273)
$yr22 \times ESG$	0.643*	0.239	0.576*	–0.260
	(0.363)	(0.365)	(0.298)	(0.267)
$yr23 \times ESG$	0.321	0.220	0.355	–0.330
	(0.347)	(0.463)	(0.282)	(0.343)
Constant	14.717	2.996	11.278	7.388
	(12.170)	(8.082)	(8.947)	(7.372)
Observations	4296	4296	4296	4296
R-squared	0.843	0.663	0.814	0.600
Number of firms	795	795	795	795
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. To maintain conciseness, the coefficients for control variables and year dummy variables are not reported in this table.

5.2 Purpose-based heterogeneity analysis

This section builds on the analyses of Bongaerts and Schoenmaker (2020) and Fatica and Panzica (2021) by investigating firms that issued ESG bonds specifically for refinancing purposes, as well as those excluding ESG bonds issued for refinancing. The literature highlights a significant observation: most green bonds are predominantly used to refinance existing green projects rather than to fund new environmental initiatives. Consequently, while such bonds may allocate resources for green purposes, they generally fail to generate new environmental improvements, making it challenging to achieve environmental additionality (Bongaerts and Schoenmaker, 2020).

As illustrated in Table 7, the interaction term $ESG \times Post$ yields statistically significant coefficients for ROA (–2.933) and ROE (8.643) for firms excluding ESG bonds used for refinancing. These results are stronger than those observed in the baseline regression, highlighting the distinct financial impact of using ESG funds for new projects. ROE increases as income from these projects boosts the numerator, while ROA declines due to the rapid growth in total assets outpacing income generation, particularly in the short term. This effect becomes more pronounced for firms investing in new projects. In contrast, firms issuing ESG bonds for refinancing purposes show no significant effects on ROA and ROE, suggesting limited financial effects from such refinancing activities.

Table 7. Financial impacts of ESG Bonds: Firms issuing for refinancing vs. excluding refinancing purposes

	Firms issuing ESG bonds for refinancing purposes		Firms excluding ESG bonds issued for refinancing purposes	
Variables	*ROA*	*ROE*	*ROA*	*ROE*
ESG			–29.168***	46.492**
			(–2.82)	(2.05)
Post	–9.312	426.206**	–5.942	–2.374
	(–0.15)	(2.11)	(–1.39)	(–0.25)
ESG × *Post*	4.816	–10.321	–2.933**	8.643***
	(1.05)	(–0.69)	(–2.20)	(2.96)
TA	0.000	0.000	0.000	–0.000
	(0.62)	(0.76)	(1.54)	(–1.04)
TL	–0.000	–0.000	–0.000	0.000
	(–0.42)	(–0.72)	(–1.19)	(0.88)
SIZE	5.223	40.859*	9.394***	1.472
	(0.69)	(1.65)	(4.04)	(0.29)
LEV	–1.243***	–1.146	–0.467***	–0.497***
	(–5.07)	(–1.34)	(–6.50)	(–3.14)
ROA	0.025	0.266	0.142***	0.683***
	(1.13)	(1.13)	(17.51)	(17.51)
CF	0.000	–0.001	0.000	–0.001
	(0.12)	(–0.54)	(0.91)	(–1.19)
CSR	–0.448	4.587*	–0.240	0.004
	(–0.53)	(1.66)	(–0.91)	(0.01)
PER	0.018**	0.043*	0.006**	0.048***
	(2.42)	(1.75)	(2.15)	(7.67)
SHARE	0.003	–0.004	0.006*	0.000
	(0.49)	(–0.25)	(1.69)	(0.00)
AGE	–1.043	–62.586**	–0.020	–0.230
	(–0.12)	(–2.16)	(–0.03)	(–0.18)
INDUSGR	0.031	0.217*	0.017*	0.047**
	(0.92)	(1.95)	(1.87)	(2.37)
Constant	94.119	2,905.946*	–65.070	51.990
	(0.19)	(1.81)	(–1.34)	(0.49)
Observations	246	246	3520	3520
Number of firms	35	35	654	654
R-squared	0.257	0.131	0.176	0.159
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. To maintain conciseness, the coefficients for year dummy variables are not reported in this table.

As illustrated in Table 8, the interaction term $ESG \times Post$ yields statistically significant coefficients for $lnscope1$ (2.514) and $lnscope12$ (1.911) in Panel A, which represents firms issuing ESG bonds for refinancing purposes. These results are significant at the 10% level and demonstrate coefficients notably higher than those observed in the baseline regression. However, the coefficients for Scope 2 and Scope 3 emissions are not statistically significant, suggesting limited or negligible effects on indirect and supply-chain-related emissions, aligning with baseline findings.

In contrast, firms excluding ESG bonds issued for refinancing purposes exhibit insignificant $ESG \times Post$ coefficients across all emission scopes, indicating no significant changes in environmental performance. This disparity highlights that ESG bonds used for refinancing purposes do not contribute to improved environmental performance or generate additional environmental benefits, as affirmed by Bongaerts and Schoenmaker (2020). Moreover, these findings indicate the potential risks of corporate greenwashing associated with the issuance of ESG bonds.

Table 8. Environmental impacts of ESG Bonds: Firms issuing for refinancing vs. excluding refinancing purposes

Variables	*lnscope*1	*lnscope*2	*lnscope*12	*lnscope*3
Panel A: Firms issuing ESG bonds for refinancing purposes				
Post	8.799	9.049	11.420	2.172
	(15.808)	(13.635)	(14.975)	(13.958)
ESG × Post	2.514*	0.165	1.911*	1.062
	(1.302)	(0.858)	(0.998)	(0.983)
SIZE	0.918	2.087	0.470	–0.184
	(2.071)	1.886)	(1.684)	(2.813)
LEV	0.0005	–0.008	0.006	–0.034
	(0.071)	(0.050)	(0.059)	(0.046)
ROA	0.003	0.012	0.002	–0.009
	(0.018)	(0.013)	(0.017)	(0.012)
ROE	–0.003	–0.007*	–0.007	0.003
	(0.006)	(0.004)	(0.005)	(0.005)
CF	–0.0001	0.0002	0.00005	–0.0001
	(0.0003)	(0.0002)	(0.0002)	(0.0001)
CSR	0.099	0.085	0.042	–0.019
	(0.204)	(0.170)	(0.154)	(0.175)
PER	0.001	–0.0003	0.002	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
SHARE	–0.002	–0.001	–0.002	–0.002*
	(0.002)	(0.001)	(0.001)	(0.001)
AGE	–1.581	–1.505	–1.906	–0.522
	(2.256)	(1.959)	(2.154)	(1.949)
INDUSGR	–0.005	0.003	–0.006	–0.008
	(0.008)	(0.006)	(0.007)	(0.007)
Constant	76.609	56.038	101.553	42.151
	(12.356)	(116.338)	(119.939)	(121.470)
Observations	247	247	247	247
Number of firms	35	35	35	35
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel B: Firms excluding ESG bonds issued for refinancing purposes				
Post	0.685	–0.404	0.245	0.020
	(0.859)	(0.716)	(0.606)	(0.620)
ESG × Post	0.306	0.258	0.298	–0.308
	(0.211)	(0.253)	(0.200)	(0.234)
SIZE	0.064	0.283	0.179	0.116
	(0.640)	(0.289)	(0.445)	(0.284)
LEV	–0.062***	–0.038***	–0.048***	–0.039***
	(0.014)	(0.011)	(0.013)	(0.014)

ROA	0.001	0.003	–0.001	–0.005
	(0.004)	(0.002)	(0.003)	(0.005)
ROE	0.0003	–0.006***	–0.003	0.003
	(0.002)	(0.001)	(0.002)	(0.002)
CF	–0.0001	0.0001*	–0.00005	–0.0001***
	(0.0001)	(0.00005)	(0.0001)	(0.00004)
CSR	0.054	0.034	0.025	0.039
	(0.060)	(0.037)	(0.059)	(0.046)
PER	–0.002*	–0.001	–0.001	–0.001
	(0.001)	(0.001)	(0.001)	(0.001)
SHARE	–0.004***	–0.001	–0.003***	–0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
AGE	–0.123	–0.016	–0.082	0.005
	(0.113)	(0.094)	(0.088)	(0.087)
INDUSGR	–0.001	0.003*	–0.001	–0.005**
	(0.002)	(0.001)	(0.002)	(0.002)
Constant	15.507	3.505	11.381	7.640
	(11.804)	(7.813)	(8.597)	(7.082)
Observations	4049	4049	4049	4049
Number of firms	760	760	760	760
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. To maintain conciseness, the coefficients for year dummy variables are not reported in this table.

6. Robustness analysis

6.1 Placebo tests

This study conducts a placebo test by randomizing the interaction term 500 times to determine whether the estimated treatment effects significantly differed from the baseline results. Table 9 summarizes the Monte Carlo permutation test results for ROA, ROE, and carbon emissions. It assesses whether the observed treatment effect is statistically significant when compared to the randomized permutations of the treatment indicator (placebo treatment).

For ROA, the observed coefficient for $ESG \times Post$ is –2.315, indicating a negative treatment effect. The one-sided test shows that only 2 out of 500 random samples produce treatment effects more extreme than the observed effect, resulting in a p-value of 0.004. This indicates a very low probability (0.4%) that such a negative treatment effect could be obtained by chance. The two-sided p-value is 0.008, further confirming the robustness of the observed effect. For ROE, the $ESG \times Post$ coefficient is 8.092, with p-values of 0 across all tests. These results validate the robustness of the positive treatment effect.

For carbon emissions, the coefficients for $lnscope1$ and $lnscope12$ show significant treatment effects, with extremely low upper-sided and two-sided p-values for the $ESG \times Post$ coefficient. For $lnscope2$ and $lnscope3$, the small p-values suggest that the permutation effects are often more significant than the baseline results.

In conclusion, the placebo tests confirm the robustness of the treatment effects for ROA, ROE, and certain carbon emission variables, demonstrating that the observed impacts are unlikely to arise by random chance.

Table 9. Monte Carlo permutation test results

$ESG \times Post$	$ESG \times Post$ (obs)	Test	c	n	p	Standard error (p)
ROA						
Coefficient	–2.314908	lower	2	500	0.004	0.003
		upper	498	500	0.996	0.003
		two-sided			0.008	0.004
ROE						
Coefficient	8.091704	lower	500	500	1.000	0.000
		upper	0	500	0.000	0.000
		two-sided			0.000	0.000
$\boldsymbol{lnscope1}$						
Coefficient	0.370	lower	500	500	1.000	0.000
		upper	0	500	0.000	0.000
		two-sided			0.000	0.000
$\boldsymbol{lnscope2}$						
Coefficient	0.170	lower	500	500	1.000	0.000
		upper	0	500	0.000	0.000
		two-sided			0.000	0.000
$\boldsymbol{lnscope12}$						
Coefficient	0.315	lower	500	500	1.000	0.000
		upper	0	500	0.000	0.000
		two-sided			0.000	0.000
$\boldsymbol{lnscope3}$						
Coefficient	–0.323	lower	0	500	0.000	0.000
		upper	500	500	1.000	0.000
		two-sided			0.000	0.000

Notes: The $ESG \times Post$ (obs) column gives the observed values of $ESG \times Post$ from the original DID regression The "c" column represents the count of permutations where the treatment effect in the placebo samples was either smaller or larger than the observed treatment effect. The "n" column shows the total number of permutations conducted in the Monte Carlo test. The "c" column represents p-values. For a lower one-sided test, $c = \#\{ ESG \times Post <= ESG \times Post\ (obs)\}$ and $p = p\_lower = c/n$. For an upper one-sided test, $c = \#\{ ESG \times Post >= ESG \times Post\ (obs)\}$ and $p = p\_upper = c/n$. For two-sided test, $p = 2^* \, min\ (p\_lower, p\_upper)$.

6.2 Analysis of the kernel matching PSM results

This study tests the robustness of the results by employing the kernel matching method to apply PSM. The parallel trend tests confirm that the pre-intervention parallel trend assumption holds for all financial and environmental performance variables (Appendix 3 and Appendix 4). Table 10 displays the DID regression results, suggesting a negative treatment effect of –2.399 for ROA and a positive treatment effect of 7.842 for ROE. These results align with findings obtained through radius matching. For environmental performance, Table 10 reports significant positive effects for $lnscope1$ and $lnscope12$, while $lnscope2$ and $lnscope3$ remain insignificant. These results further verify the robustness of the initial findings.

Table 10. Regression analysis results using kernel PSM

Variables	(1) *ROA*	(2) *ROE*	(3) *lnscope*1	(4) *lnscope*2	(5) *lnscope*12	(6) *lnscope*3
ESG	–28.964***	45.547**	0.333	–0.435	0.262	0.976
	(–2.84)	(1.99)	(2.337)	(1.440)	(1.925)	(2.042)
Post	–6.341	–1.843	0.668	–0.428	0.236	–0.010
	(–1.51)	(–0.20)	(0.879)	(0.703)	(0.631)	(0.626)
ESG × *Post*	–2.399**	7.842***	0.490***	0.187	0.432***	–0.239
	(–2.12)	(3.09)	(0.182)	(0.271)	(0.159)	(0.211)
Constant	–63.355	46.465	14.788	2.920	11.276	7.667
	(–1.35)	(0.44)	(12.133)	(7.993)	(8.855)	(7.275)
Observations	3766	3766	4296	4296	4296	4296
R-squared	0.172	0.149	0.843	0.654	0.814	0.602
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Number of firms	689	689	795	795	795	795

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. To maintain conciseness, the coefficients for control variables and year dummy variables are not reported in this table.

7. Discussion and conclusion

Based on data from 795 Japanese listed firms, this study examines the effects of the Green Bond Guidelines 2020 on the financial and environmental performance of these firms, employing a combination of PSM and DID methodologies.

Regarding financial performance, the findings indicate that after the implementation of the Green Bond Guidelines, firms that issued ESG bonds have significantly decreased ROA compared to those that did not. When firms issue ESG bonds, their total assets (the denominator) increase because the funds raised through the bonds are added to the balance sheet as assets. However, if the income generated by the new projects (the numerator) does not grow fast enough to match the increase in total assets, ROA will decrease. This reflects the fact that the firm's overall profitability relative to its larger asset base has declined. This outcome aligns with portfolio theory, which suggests that limitations on investment scope can negatively impact financial performance. These results are consistent with studies by Yeow and Ng (2021), Gavin et al. (2022), and Chen et al. (2023).

Conversely, the findings reveal that firms issuing ESG bonds experience significantly higher ROE after the guidelines were introduced, suggesting a positive effect on this financial metric. When firms issue ESG bonds, they often use the borrowed funds to finance projects or investments. These activities can increase the firm's net income, the numerator in the ROE formula. However, issuing bonds does not directly affect shareholders' equity (the denominator in the ROE formula) because bonds are a form of debt, not equity. As a result, an increase in net income leads to a higher ROE. This finding supports most literature on the relationship between ESG performance and CFP, including works by Ferrell et al. (2016), Flammer (2015), Orlitzky (2001), Przychodzen and Przychodzen (2015), and Tsai and Wu (2022). It underscores the role of ESG bonds in easing financing constraints.

To sum up, the Green Bond Guidelines 2020 influence firms issuing ESG bonds by affecting key financial metrics differently. It leads to an increase in net income (higher ROE), but the increase in total assets due to borrowing can outpace the income growth (lower ROA). This happens because the bonds expand the firm's asset base while keeping shareholders' equity constant, creating a divergence between these two metrics.

In addition, the financial impact depends on the purpose of the ESG bonds. For firms using ESG bonds for refinancing purposes, the effect on ROA and ROE is negligible, indicating limited financial implications. In contrast, for firms issuing ESG bonds to invest in new projects, the effects on both ROA and ROE are stronger than the baseline regression results, underscoring the significant role of new-project-driven ESG financing in shaping financial performance.

Moreover, firms operating in rapidly growing industries, as well as those with higher PER, tend to achieve better performance in terms of both ROA and ROE. In contrast, increased leverage is linked to lower ROA and ROE. The heterogeneity analysis shows that the impact of the policy guidance on CFP exhibits significant time variation. While the guidelines have an immediate positive impact on ROE in 2020, a negative impact on ROA is not observed until 2022, indicating a lagged response in ROA.

This study evaluates environmental performance through carbon emissions, focusing on Scope 1, Scope 2, $Scope12$, and Scope 3 emissions. The findings reveal that firms issuing ESG bonds do not achieve significant reductions in carbon emissions. Instead, Scope 1 and $Scope12$ emissions increase significantly, while Scope 2 and Scope 3 emissions show no significant changes when compared to firms that did not issue ESG bonds. These results suggest a disconnect between ESG bond issuance and actual emissions reduction efforts, consistent with the findings of Wei et al. (2022) and Bongaerts and Schoenmaker (2020). Control variables reveal that higher leverage reduces emissions across all types, while $SHARE$ and PER are associated with reductions in Scope 1 emissions, particularly in firms with higher ownership and valuation ratios.

Moreover, this study reveals that environmental performance varies depending on the purpose of ESG bond issuance. However, the results indicate that neither ESG bonds used for refinancing nor those allocated to new projects lead to improved environmental performance, with both failing to achieve environmental additionality.

These findings highlight several challenges associated with ESG bonds in Japan. First, there is a significant risk of greenwashing. Due to inconsistent ratings across different rating agencies for ESG bonds, it is difficult to accurately assess and verify the environmental impact of ESG bonds. This issue exacerbates the potential for firms to exaggerate or misrepresent their environmental initiatives, as noted by Benlemlih et al. (2022), Fatica and Panzica (2021), Flammer (2020), and Yeow and Ng (2021).

Second, similar to the observations by Bongaerts and Schoenmaker (2020) on green bonds, Japan's ESG bonds demonstrate a lack of additionality. These bonds often refinance existing projects, originally funded by conventional bonds, rather than financing new environmental initiatives. This approach limits their ability to deliver incremental environmental benefits, as such projects would likely continue regardless of refinancing.

Third, the decentralized issuance of green bonds reduces their liquidity, while low yields and high issuance and reporting costs further increase the effective cost of financing (Bongaerts and Schoenmaker, 2020). These challenges make ESG bonds, particularly green bonds, less appealing for funding new projects, thereby diminishing their potential to achieve additionality and meaningful environmental impact.

8. Implications

For investors, these findings reflect the importance of assessing the diverse impacts of ESG bond issuances on different financial metrics. Investors should consider not only the immediate stock market reactions but also the impacts on firms' operational performance and asset utilization. This can help make more informed investment decisions that balance financial returns with sustainability goals.

The effect of Green Bond Guidelines 2020 in reducing carbon emissions remains limited, suggesting a significant risk of greenwashing. This calls for stricter monitoring, standardization of environmental impact assessments, and measures to ensure that ESG bonds contribute meaningfully to sustainability goals. Regulators and certification bodies should enhance the scrutiny, such as reporting requirements and verification mechanisms of ESG claims for ESG bond issuers.

Moreover, the findings emphasize that ESG bonds used for refinancing fail to improve financial performance and environmental outcomes, whereas those financing new projects show greater effects on ROA and ROE. This highlights the need for targeted policies or regulatory frameworks to incentivize additionality and address inefficiencies in Japan's ESG bond market. Examples include innovative mechanisms such as green certificates (Bongaerts and Schoenmaker, 2020) and initiatives that link ESG bonds to new ESG projects.

Furthermore, many firms fail to disclose ESG data, and inconsistencies in reported emissions make it hard to accurately and comprehensively measure their environmental performance. This lack of clarity increases information gaps for investors and policymakers. To address these challenges, policymakers should standardize ESG reporting and improve transparency. Establishing uniform data requirements will improve the accuracy and comparability of disclosed information, which allows for a more accurate assessment of a firm's true environmental impact.

References

Albareda, L., Lozano, J. M., & Ysa, T. (2007) "Public Policies on Corporate Social Responsibility: The Role of Governments in Europe," *Journal of Business Ethics,* 74(4), 391–407. https://doi.org/10.1007/s10551-007-9514-1

Allen, F., & Yago, G. (2011) "Environmental Finance: Innovating to Save the Planet," *Journal of Applied Corporate Finance,* 23(3), 99–111. https://doi.org/10.1111/j.1745-6622.2011.00347.x

Aruga, K. (2024) "Are Retail Investors Willing to Buy Green Bonds? A Case for Japan," *Journal of Sustainable Finance & Investment*, 1–15. https://doi.org/10.1080/20430795.2024.2349723

Azur, M. J., Stuart, E. A., Frangakis, C., & Leaf, P. J. (2011) "Multiple Imputation by Chained Equations: What Is It and How Does It Work?" *International Journal of Methods in Psychiatric Research*, 20(1), 40–49. https://doi.org/10.1002/mpr.329

Baker, M. P., Bergstresser, D. B., Serafeim, G., & Wurgler, J. A. (2018) "Financing the Response to Climate Change: The Pricing and Ownership of U.S. Green Bonds," *NBER Working Papers*, 25194. https://doi.org/10.2139/ssrn.3275327

Baulkaran, V. (2019) "Stock Market Reaction to Green Bond Issuance," *Journal of Asset Management*, 20(5), 331–340. https://doi.org/10.1057/s41260-018-00105-1

Becker, S. O., & Ichino, A. (2002) "Estimation of Average Treatment Effects Based on Propensity Scores," *The Stata Journal: Promoting Communications on Statistics and Stata*, 2(4), 358–377. https://doi.org/10.1177/1536867x0200200403

Benlemlih, M., Jaballah, J., & Kermiche, L. (2022) "Does Financing Strategy Accelerate Corporate Energy Transition? Evidence from Green Bonds," *Business Strategy and the Environment*, 32(1) https://doi.org/10.1002/bse.3180

Bhaskaran, R. K., Ting, I. W. K., Sukumaran, S. K., & Sumod, S. D. (2020) "Environmental, Social, and Governance Initiatives and Wealth Creation for Firms: An Empirical Examination," *Managerial and Decision Economics*, 41(5), 710–729. https://doi.org/10.1002/mde.3131

Bongaerts, D., & Schoenmaker, D. (2020) "The Next Step in Green Bond Financing," *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3389762

Chen, S., Yu, S., & Gao, P. (2023) "Environmental, Social, and Governance (ESG) Performance and Financial Outcomes: Analyzing the Impact of ESG on Financial Performance," *Journal of Environmental Management*, 345(1), 118829–118829. https://doi.org/10.1016/j.jenvman.2023.118829

Collins, L. M., Schafer, J. L., & Kam, C.-M. (2001) "A Comparison of Inclusive and Restrictive Strategies in Modern Missing Data Procedures," *Psychological Methods*, 6(4), 330–351. https://doi.org/10.1037/1082-989x.6.4.330

Environmental Finance. (2023) *Sustainable Bonds Insight* 2023. Retrieved from https://www.environmental-finance.com/assets/files/research/sustainable-bonds-insight-2023.pdf. (Accessed October 10, 2024)

Fama, E. F. (1970) "Efficient Capital Markets: A Review of Theory and Empirical Work," *The Journal of Finance*, 25(2), 383–417. https://doi.org/10.2307/2325486

Fama, E. F. (1991) "Efficient Capital Markets: II," *The Journal of Finance*, 46(5), 1575–1617. https://doi.org/10.1111/j.1540-6261.1991.tb04636.x

Fatemi, A., Glaum, M., & Kaiser, S. (2018) "ESG Performance and Firm Value: The Moderating Role of Disclosure," *Global Finance Journal*, 38, 45–64. https://doi.org/10.1016/j.gfj.2017.03.001

Fatica, S., & Panzica, R. (2021) "Green Bonds as a Tool Against Climate Change?" *Business Strategy and the Environment*, 30(5) https://doi.org/10.1002/bse.2771

Ferrell, A., Liang, H., & Renneboog, L. (2016) "Socially Responsible Firms," *Journal of Financial Economics*, 122(3), 585–606. https://doi.org/10.1016/j.jfineco.2015.12.003

Flammer, C. (2015) "Does Corporate Social Responsibility Lead to Superior Financial Performance? A Regression Discontinuity Approach," *Management Science*, 61(11), 2549–2568. https://doi.org/10.1287/mnsc.2014.2038

Flammer, C. (2020) "Green Bonds: Effectiveness and Implications for Public Policy," *Environmental and Energy Policy and the Economy*, 1, 95–128. https://doi.org/10.1086/706794

Friede, G., Busch, T., & Bassen, A. (2015) "ESG and Financial Performance: Aggregated Evidence from More Than 2000 Empirical Studies," *Journal of Sustainable Finance & Investment*, 5(4), 210–233. https://doi.org/10.1080/20430795.2015.1118917

Friedman, M. (1970) "The Social Responsibility of Business Is to Increase Its Profits," Retrieved from https://

www.nytimes.com/1970/09/13/archives/a-friedman-doctrine-the-social-responsibility-of-business-is-to.html

Fu, Y., He, C., & Luo, L. (2021) "Does the Low-Carbon City Policy Make a Difference? Empirical Evidence of the Pilot Scheme in China with DEA and PSM-DID," *Ecological Indicators*, 122, 107238. https://doi.org/10.1016/j.ecolind.2020.107238

Gavin, M., Coelho, M. T. P., McGlinch, J., & Henisz, W. J. (2022) "Pathways to Materiality: Environmental, Social & Governance (ESG) Factors and Financial Performance," *Academy of Management Proceedings*, 2022(1) https://doi.org/10.5465/ambpp.2022.16003abstract

Gianfrate, G., & Peri, M. (2019) "The Green Advantage: Exploring the Convenience of Issuing Green Bonds," *Journal of Cleaner Production*, 219, 127–135. https://doi.org/10.1016/j.jclepro.2019.02.022

Glavas, D. (2020) "How Do Stock Prices React to Green Bond Issuance Announcements?" *Finance*, 41(1), 7–51. https://doi.org/10.2139/ssrn.3279069

Graham, J. W. (2009) "Missing Data Analysis: Making It Work in the Real World," *Annual Review of Psychology*, 60(1), 549–576. https://doi.org/10.1146/annurev.psych.58.110405.085530

Hartzmark, S. M., & Sussman, A. B. (2017) "Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows," *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3016092

Jakubik, P., & Uguz, S. (2021) "Impact of Green Bond Policies on Insurers: Evidence from the European Equity Market," *Journal of Economics and Finance*, 45(2), 381–393. https://doi.org/10.1007/s12197-020-09534-4

Japan Exchange Group. (2023) ESG Bonds | *Japan Exchange Group*, Retrieved from https://www.jpx.co.jp/english/equities/products/tpbm/green-and-social-bonds/index.html (Accessed October 20, 2024)

Kofman, P., & Sharpe, I. G. (2003) "Using Multiple Imputation in the Analysis of Incomplete Observations in Finance," *Journal of Financial Econometrics*, 1(2), 216–249. https://doi.org/10.1093/jjfinec/nbg013

Li, Y., Gong, M., Zhang, X.-Y., & Koh, L. (2018) "The Impact of Environmental, Social, and Governance Disclosure on Firm Value: The Role of CEO Power," *The British Accounting Review*, 50(1), 60–75. https://doi.org/10.1016/j.bar.2017.09.007

Ministry of the Environment of Japan. (2020) *Green Bond Guidelines* 2020. Retrieved from https://www.env.go.jp/content/000042342.pdf (Accessed August 10, 2024)

Murphy, G. B., Trailer, J. W., & Hill, R. C. (1996) "Measuring Performance in Entrepreneurship Research," *Journal of Business Research*, 36(1), 15–23. https://doi.org/10.1016/0148-2963(95)00159-x

Nanayakkara, M., & Colombage, S. (2019) "Do Investors in Green Bond Market Pay a Premium? Global Evidence," *Applied Economics*, 51(40), 4425–4437. https://doi.org/10.1080/00036846.2019.1591611

Ordonez - Borrallo, R., Ortiz - de - Mandojana, N., & Delgado - Ceballos, J. (2024) "Green Bonds and Environmental Performance: The Effect of Management Attention," *Corporate Social-Responsibility and Environmental Management*. https://doi.org/10.1002/csr.2858

Orlitzky, M. (2001) "Does Firm Size Confound the Relationship Between Corporate Social Performance and Firm Financial Performance?" *Journal of Business Ethics*, 33(2), 167–180. https://doi.org/10.1023/a:1017516826427

Przychodzen, J., & Przychodzen, W. (2015) "Relationships Between Eco-Innovation and Financial Performance – Evidence from Publicly Traded Companies in Poland and Hungary," *Journal of Cleaner Production*, 90, 253–263. https://doi.org/10.1016/j.jclepro.2014.11.034

Quinche-Martín, F. L., & Cabrera-Narváez, A. (2020) "Exploring the Potential Links Between Social and Environmental Accounting and Political Ecology," *Social and Environmental Accountability Journal*, 40(1), 53–74. https://doi.org/10.1080/0969160x.2020.1730214

Raghunathan, T., Lepkowski, J., Hoewyk, J. V., & Solenberger, P. W. (2000) "A Multivariate Technique for Multiply Imputing Missing Values Using a Sequence of Regression Models," *Survey Methodology*, 27(1) Retrieved from https://www.researchgate.net/publication/244959137

Revelli, C., & Viviani, J.-L. (2014) "Financial Performance of Socially Responsible Investing (SRI): What Have We Learned? A Meta-Analysis," *Business Ethics: A European Review*, 24(2), 158–185. https://doi.org/10.1111/beer.12076

Riedl, A., & Smeets, P. (2017) "Why Do Investors Hold Socially Responsible Mutual Funds?" *The Journal of Finance*, 72(6), 2505–2550. https://doi.org/10.1111/jofi.12547

Rosenbaum, P. R., & Rubin, D. B. (1983) "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 70(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Roslen, S. N. M., Yee, L. S., & Ibrahim, S. A. B. (2017) "Green Bond and Shareholders' Wealth: A Multi-Country Event Study," *International Journal of Globalization and Small Business*, 9(1), 61. https://doi.org/10.1504/ijgsb.2017.084701

Rubin, D. B. (1987) *Multiple Imputation for Nonresponse in Surveys*, John Wiley.

Rubin, D. B., & Thomas, N. (1992) "Affinely Invariant Matching Methods with Ellipsoidal Distributions," *The Annals of Statistics*, 20(2), 1079–1093. https://doi.org/10.2307/2241998

Schafer, J. L., & Graham, J. W. (2002) "Missing Data: Our View of the State of the Art," *Psychological Methods*, 7(2), 147–177. https://doi.org/10.1037/1082-989x.7.2.147

Schenker, N., & Taylor, J. M. G. (1996) "Partially Parametric Techniques for Multiple Imputation," *Computational Statistics & Data Analysis*, 22(4), 425–446. https://doi.org/10.1016/0167-9473(95)00057-7

Schröder, M. (2014) "Financial Effects of Corporate Social Responsibility: A Literature Review," *Journal of Sustainable Finance & Investment*, 4(4), 337–350. https://doi.org/10.1080/20430795.2014.971096

Stuart, E. A. (2010) "Matching Methods for Causal Inference: A Review and a Look Forward," *Statistical Science*, 25(1), 1–21. https://doi.org/10.1214/09-sts313

Tsai, H.-J., & Wu, Y. (2022) "Changes in Corporate Social Responsibility and Stock Performance," *Journal of Business Ethics*, 178, 735–755. https://doi.org/10.1007/s10551-021-04772-w

van Buuren, S. (2007) "Multiple Imputation of Discrete and Continuous Data by Fully Conditional Specification," *Statistical Methods in Medical Research*, 16(3), 219–242. https://doi.org/10.1177/0962280206074463

Wang, J., Chen, X., Li, X., Yu, J., & Zhong, R. (2020) "The Market Reaction to Green Bond Issuance: Evidence from China," *Pacific-Basin Finance Journal*, 60, 101294. https://doi.org/10.1016/j.pacfin.2020.101294

Wei, P., Li, Y., & Zhang, Y. (2022) "Corporate Green Bonds and Carbon Performance: An Economic Input–Output Life Cycle Assessment Model ‐ Based Analysis," *Business Strategy and the Environment*, 32(6) https://doi.org/10.1002/bse.3267

Weston, P., & Nnadi, M. (2021) "Evaluation of Strategic and Financial Variables of Corporate Sustainability and ESG Policies on Corporate Finance Performance," *Journal of Sustainable Finance & Investment*, 13(2), 1–17. https://doi.org/10.1080/20430795.2021.1883984

Yeow, P. S., & Ng, T. S. (2021) "Do Green Bond Certifications Create Value? Evidence from Chinese Green Bond Market," *Journal of Sustainable Finance & Investment*, 11(4), 300–318. https://doi.org/10.1080/20430795.2020.1845775

Yoon, B., Lee, J., & Byun, R. (2018) "Does ESG Performance Enhance Firm Value? Evidence from Korea," *Sustainability*, 10(10), 3635. https://doi.org/10.3390/su10103635

Zerbib, O. D. (2019) "The Effect of Pro-Environmental Preferences on Bond Prices: Evidence from Green Bonds," *Journal of Banking & Finance*, 98, 39–60. https://doi.org/10.1016/j.jbankfin.2018.10.012

Zhou, X., & Cui, Y. (2019) "Green Bonds, Corporate Performance, and Corporate Social Responsibility," *Sustainability*, 11(23), 6881. https://doi.org/10.3390/su11236881

Appendix

Appendix 1. Balance test results of variables before and after radius matching (ROA)

Variable	Unmatched	Mean			%reduct	t-test	
	Matched	Treated	Control	%bias	|bias|	t	p>|t|
TA	U	6.1e+06	1.5e+06	46.0		15.66	0.000
	M	6.1e+06	5.3e+06	8.5	81.6	1.39	0.164
TL	U	5.1e+06	1.2e+06	41.7		14.37	0.000
	M	5.1e+06	4.3e+06	7.9	81.0	1.31	0.191
SIZE	U	14.412	12.234	123.7		28.73	0.000
	M	14.412	14.347	3.7	97.0	0.78	0.436
LEV	U	68.475	53.45	81.5		19.11	0.000
	M	68.475	68.264	1.1	98.6	0.22	0.825
CF	U	1964.9	2047.3	–7.1		–1.73	0.083
	M	1964.9	1955.9	0.8	89.1	0.15	0.883
CSR	U	4.1932	4.052	5.9		1.37	0.170
	M	4.1932	4.2836	–3.8	35.9	–0.75	0.453
PER	U	192.79	186.49	6.0		1.50	0.133
	M	192.79	196.28	–3.3	44.6	–0.62	0.535
SHARE	U	305.75	411.36	–58.7		–14.34	0.000
	M	305.75	316.64	–6.0	89.7	–1.20	0.229
AGE	U	66.999	69.176	–7.3		–1.88	0.061
	M	66.999	68.651	–5.6	24.1	–1.00	0.319
INDUSGR	U	6.1468	8.843	–8.7		–2.09	0.037
	M	6.1468	6.3327	–0.6	93.1	–0.13	0.900

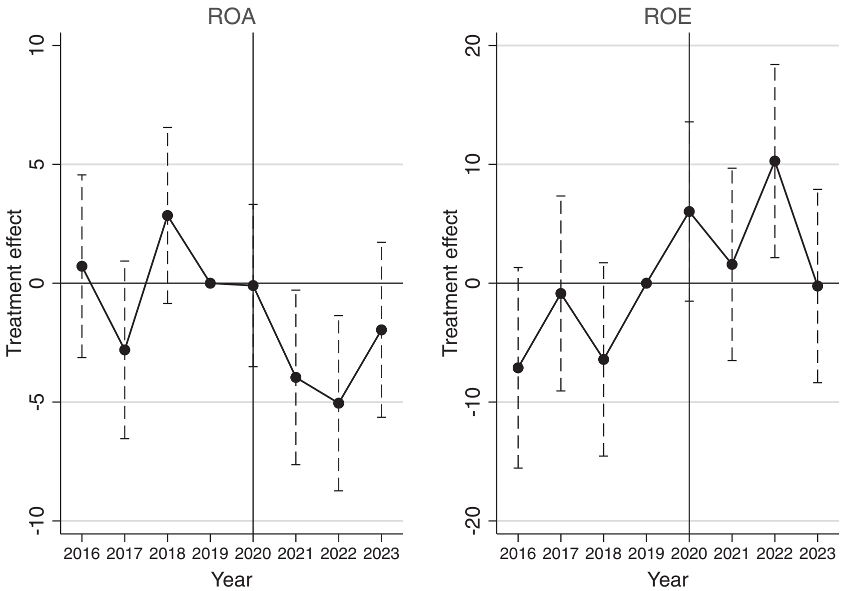
Notes: U represents unmatched, and M represents matched.

Appendix 2. Balance test results of variables before and after kernel matching (ROE)

Variable	Unmatched	Mean			%reduct	t-test	
	Matched	Treated	Control	%bias	|bias|	t	p>|t|
TA	U	6.1e+06	1.5e+06	46.0		15.66	0.000
	M	6.1e+06	5.3e+06	8.4	81.8	1.37	0.170
TL	U	5.1e+06	1.2e+06	41.7		14.37	0.000
	M	5.1e+06	4.4e+06	7.8	81.2	1.29	0.197
SIZE	U	14.412	12.234	123.7		28.73	0.000
	M	14.412	14.355	3.3	97.3	0.69	0.487
LEV	U	68.475	53.45	81.5		19.11	0.000
	M	68.475	68.301	0.9	98.8	0.18	0.856
CF	U	1964.9	2047.3	–7.1		–1.73	0.083
	M	1964.9	1955.2	0.8	88.2	0.16	0.874
CSR	U	4.1932	4.052	5.9		1.37	0.170
	M	4.1932	4.2875	–3.9	33.2	–0.78	0.434
PER	U	192.79	186.49	6.0		1.50	0.133
	M	192.79	196.23	–3.3	45.4	–0.61	0.541
SHARE	U	305.75	411.36	–58.7		–14.34	0.000
	M	305.75	316.28	–5.8	90.0	–1.16	0.245
AGE	U	66.999	69.176	–7.3		–1.88	0.061
	M	66.999	68.632	–5.5	25.0	–0.99	0.325
INDUSGR	U	6.1468	8.843	–8.7		–2.09	0.037
	M	6.1468	6.3574	–0.7	92.2	–0.14	0.887

Notes: U represents unmatched, and M represents matched.

Appendix 3. Parallel trend test results for financial impacts (kernel PSM)



Appendix 4. Parallel trend test results for environmental impacts (kernel PSM)