Do Lenders Price SMEs' Pollution?*

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Abstract

This paper examines whether and how lenders incorporate the environmental performance of private small and medium-sized enterprises (SMEs) into debt pricing. Using private information on corporate waste to quantify a significant component of Danish SMEs' pollution, I show that SMEs with less waste pollution have a lower cost of debt, and that lenders provide this lower cost of debt to firms with inherently less pollution. The pricing effect is robust to an instrumental variable approach and more pronounced when SMEs obtain new debt. These findings suggest lenders incorporate SMEs' environmental performance into debt pricing without publicly available environmental disclosures and databases, and that lenders focus on managing risk through selection rather than promoting SMEs' green transition.

Keywords: Cost of debt, ESG, financing policy, waste

JEL Codes: G32, G33, M41, Q56

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1 Introduction

Small- and medium-sized enterprises (SMEs) cause about 40% of all corporate pollution, including corporate carbon emissions.[1] To reduce SMEs' pollution, regulators pressure lenders to incorporate climate and other environmental considerations into their lending decisions.[2] Regulators believe lenders can promote firms' transition to more sustainable activities because of lenders' superior information-gathering and monitoring abilities and their financial incentives to manage and intermediate environmental risks (Conley and Williams, 2011). For example, banks offer green loans to firms and sell them as green bonds to environmentally conscious investors. However, lenders argue this is difficult for smaller firms due to the lack of reliable data and they have risk management incentives to focus on the level of exposure to borrowers' environmental risks. These factors raise doubts about whether and how lenders perform this intermediary role for smaller firms' environmental risk.

Understanding the effect of SMEs' pollution on debt pricing is important for two main reasons. First, SMEs typically lack behind in the adaption of sustainability technologies. Unawareness, lack of expertise and resources, and the "too-small-to-matter" argument rank as the dominant barriers for SMEs to improve their environmental impact (see Johnson and Schaltegger, 2016). Relatedly and second, regulators largely refrain from imposing sustainability regulation directly on SMEs whereas their public and large counterparts face increasing regulatory demand for sustainability transparency and pricing, especially in Europe with the European Sustainability Reporting Standards and EU Emissions Trading Scheme. That is because information generation, acquisition, and monitoring costs are proportionally higher relatively to SMEs' environmental harm and the static nature of these costs. Overall,

[1] https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/10/assessing-greenhouse-gas-emissions-and-energy-consumption-in-smes_002d1637/ac8e6450-en.pdf

[2] The ECB recently published guidelines on how lender banks should incorporate climate-related and environmental risk into their core practices, including their risk frameworks and nonfinancial reporting. In 2022, the ECB performed its first climate-related stress test of banks' balance sheets. See https://www.bankingsupervision.europa.eu/press/pr/date/2022/html/ssm.pr220127~bd20df4d3a.en.html. Perrault and Giraud (2022) reports that several U.S. regulators have prepared similar mandates for large U.S. lenders. See also Acharya et al. (2023). In addition, lenders' environmental impact faces more public scrutiny and pressure from other stakeholders.

SMEs' sustainability efforts and lenders' incentives and costs to affect these differ compared to large and public firms.

To examine whether and how lenders price SMEs' pollution into debt, I exploit firm-level information on Danish SMEs' waste pollution from 2011 to 2021 to measure their environmental performance. This setting is ideal for understanding lenders' role in monitoring, managing, and intermediating SMEs' environmental risk when reliable data is absent. Despite limited research in finance and accounting investigates corporate waste, it constitutes a significant source of firms' pollution, including part of their carbon emissions (Themelis and Ulloa, 2007; Kaza et al., 2018). The waste data originates from fillings by third-party waste collectors to the Danish Environmental Protection Agency (DEPA). The data covers industrial waste of all firm sizes and is held confidentially by the DEPA. The setting also allays bias concerns related to managers' discretion. Waste collectors must undergo certification and face penalties if they file late or incorrectly. Thus, the data represents a reliable source of firms' pollution, which is publicly unobservable.

I begin my analysis by examining whether SMEs' environmental performance is associated with the cost of debt. Following the approach laid out in the literature, I find that a within-group one-standard-deviation change in the intensity of the SMEs' environmental impact is associated with a 1.6–3.1 basis points change in the cost of debt, depending on the waste treatment and type. These results suggest that lenders exercise their intermediating and risk management role by pricing sustainability in smaller firms and are robust to alternative definitions of SMEs' cost of debt and pollution. The cost of debt effects in my study are 1–14 basis points lower than that documented in studies of larger firms (Huynh and Xia, 2021; Ehlers et al., 2022; Altavilla et al., 2024).[3] Moreover, the cost of debt levels align with the findings of Feldhütter et al. (2024) which documents that bond investors are willing to forego a spread of 1–2 basis points when investing in sustainability-linked loans.

To corroborate that the results reflect lenders' environmental preferences, I examine the

[3]This interval is calculated using the sample standard deviation rather than the within-group standard deviation as other studies do not report the latter.

relationship between the degree of harm from a firm's waste production, and the lending terms. Specifically, I classify waste according to its environmental impact and examine whether lenders assign different weights to these categories when determining debt pricing. If lenders value borrowers' environmental performance lenders should demand a higher price when SMEs' produce more harmful waste. The results show that the relationship between firms' environmental impact and the cost of debt is monotonically higher when waste imposes a high ecological impact. More specifically, I find that the cost of debt is higher for incineration and landfill disposal relative to recycling. I also find that the coefficient for hazardous waste is more than ten times that for nonhazardous waste; and unsorted waste intensity estimate has a stronger association with the cost of debt than sorted waste. Although differences in coefficient estimates between treatment and sorting intensities are insignificant at conventional levels, these findings suggest that my construct captures lenders' environmental preferences.

Subsequently, I implement a two-stage least squares (2SLS) approach to alleviate endogeneity concerns. I use changes in firms' access to waste treatment facilities as an instrument variable for SMEs' waste generation. First, I show that SMEs' waste outputs and decisions to recycle are associated with SMEs' distances to waste-type and treatment-specific facilities. Danish regulation requires all firms to handle their waste appropriately and farther distances to waste treatment facilities strengthen firms' incentives to reduce waste outputs. Access to waste facilities is thus pertinent to SMEs' decisions to generate waste and fulfills the relevance criterion. Then, I observe firm-specific variation in access to waste facilities from waste treatment firms expanding their operations, opening new facilities, or collapsing while considering industry and geographical conditions over time. The inherent link between firms' decision to produce waste and their operations challenges the exclusion criterion if less waste increases operation costs. In a sub-analysis, I do not find that access to fewer waste facilities is associated with lower earnings before interest (i.e., higher costs), which goes against differences in operating costs from changes to waste outputs explaining the cost of debt and indicates that the exclusion criterion is met. The 2SLS estimation results are consistent with lenders' preferences for SMEs with less pollution.

Next, I seek to understand how lenders exert their environmental preferences. Specifically, I try to gauge whether lenders exhibit selection behavior by providing a higher cost of debt to SMEs with more pollution or whether lenders promote SMEs' green transition by pricing the improvements in SMEs' environmental performance (see Kacperczyk and Peydró, 2024). On the one hand, lenders have incentives to manage and limit their exposure to risks, including those arising from firms' environmental activities. Research on larger public firms suggests that firms' environmental impact is associated with material risks, including litigation, regulation, compliance, transition, and regime-change risk (Albuquerque et al., 2019; Bolton and Kacperczyk, 2021; Chava, 2014; Hsu et al., 2023). Despite SMEs experiencing less public scrutiny and being exempt from environmental disclosure requirements, SMEs likely still face these environmental risks.

On the other hand, lenders claim that they engage in improving firms' environmental performance, irrespective of firms' existing pollution levels.[4] For example, banks offer green loans to firms that are tied to investments in environmental improvements, and which lenders subsequently sell them in green bonds to investors with environmental preferences at premium (Feldhütter et al., 2024). However, fixed costs of monitoring firms' environmental

[4] The three largest banks in Denmark and several of the largest banks in the U.S. describe their financing policies to offering financial products tied to improvements of firms' environmental performance. Danske Bank, the largest Danish bank, describes waste reduction in terms of its weight as a metric for assessing environmentally enhancing projects. https://danskebank.com/-/media/danske-bank-com/pdf/investor-relations/debt/green-bonds/danske-bank-green-finance-framework-november-2022.pdf. Nordea Bank, which is the second largest corporate lender in Denmark, presents "waste management, including waste prevention, reduction, collection, treatment, recycling, and processing (excluding hazardous waste)" as project types in their green funding framework https://www.nordea.com/en/doc/nordea-green-funding-framework-december-2023-0.pdf. The third largest bank in Denmark, Jyske Bank describes waste reduction and recycling as eligible criteria for their green lending framework https://jyskebank.com/wps/wcm/connect/jbc/f5080b57-8cb8-4cf9-807c-1ebc452ec689/Jyske+Bank+Group+Green+Finance+Framework+2022+November.pdf?MOD=AJPERES&CVID=oTFw2nO. The largest corporate lenders promote two cases about the recycling of firms' waste. See cases at https://nytfranordea.nordea.dk/da/artikler/der-findes-ikke-noget-i-hele-verden-der-er-mere-sexet-end-denne-her-forretning and https://danskebank.dk/erhverv/seneste-nyt/2022/nyt-liv-til-madrasserne (both in Danish). U.S. examples include Bank of America, Citi Group, JP Morgan Chase, and Well's Fargo.

activities may reduce the financial benefits of providing green loans to SMEs, and such financing products only promotes green transition if the proceeds influences firms to implement greener operation alternatives than other investment opportunities. If not, lenders' issuance of green bonds serves as nothing more than labeling financing to firms already engaged or willing to engage in more environmentally responsible activities.

To examine how lenders exert their environmental preferences, I exploit variation across fixed effect structures. The main estimations include industry- and municipality-year fixed effects to account for time-varying effects of industry trends, local and industry-specific economic conditions, and local waste regulation. This tight fixed effect structure reduces the variation to across- and within-firm differences in SMEs' waste pollution and cost of debt under the assumption that it captures omitted confounders and other endogenous factors.[5] The results of 2SLS results indicates that endegeneity issues do not explain the results. Then, by adding firm fixed effects, I practically remove any selection behavior as it eliminates across-firm variation and SMEs' average levels of cost of debt and pollution (see Breuer and DeHaan, 2024).

The link between SMEs' pollution and the cost of debt is highly attenuated and insignificant when I include firm fixed effects. These results suggest that lenders exercise selection by comparing SMEs' waste pollution across firms rather than promoting individual SMEs' green transition. However, it is important to recognize that despite these methodological efforts, omitted variable bias and other endogeneity issues may still arise if unobserved factors influencing both SMEs' pollution levels and their cost of debt are not fully captured by the fixed effects or the instrumental variable approach.

Following the main analysis, I examine the association between SMEs' pollution levels and the cost of debt when they obtain new debt. When firms apply for credit, lenders collect relevant information to assess risk, enabling them to structure and price debt according to their risk management and environmental preferences. If pollution information is pertinent

[5]The main results rely on two-digit and are robust to using four-digit NACE industry codes.

to evaluate firm risk and against lenders' preferences, I expect a stronger relationship between SMEs' pollution levels and their debt costs upon acquiring new credit. The findings of the analysis align with this prediction.

This study makes two main contributions. First, it adds to the literature on lenders' monitoring role. I demonstrate that lenders incorporate SMEs' environmental impact into debt prices despite the absence of transparency regulation and public information on SMEs' environmental activities. These findings corroborate that lenders monitor firms' environmental performance, consistent with Amiram et al. (2023), Choy et al. (2024), and Lee and Zakota (2024), and illustrate that lenders incorporate firms' environmental performance into lending decisions based on information channels other than public environmental disclosures. To date, studies addressing the link between firms' environmental performance and their cost of capital rely on public disclosures or databases (Amiram et al., 2023; Bolton and Kacperczyk, 2021; Chava, 2014; Ilhan et al., 2021; Hsu et al., 2023; Seltzer et al., 2024; Sharfman and Fernando, 2008). However, the revelation of firms' environmental activities to the public has important capital market and real effects, which raises uncertainty of whether the results of the related studies are consistent in the absence of public scrutiny (Downar et al., 2021; Krueger et al., 2024; Tomar, 2023).[6]

Second, this study contributes to the literature on lenders' preferences for environmentally responsible firms. To my knowledge, this is the first study to investigate the consequences of firms' environmental performance on a country-wide sample of smaller firms and across waste substances. Specifically, I find that SMEs enjoy a lower cost of debt when their operations deliver lower environmental impact. This finding is consistent with the work of Sharfman and Fernando (2008), Chava (2014), Amiram et al. (2023), and Altavilla et al. (2024) on large public firms. Moreover, I find results consistent with lenders exercising selection by offering a lower cost of debt to firms with lower ecological footprints, and that SMEs obtaining new debt increases lenders' weight on waste when pricing debt (Kacperczyk and Peydró, 2024).

[6] Griffin et al. (2017) find no effect of greenhouse gas emissions disclosures on the pricing of such emissions but argues that investors can derive relevant information from other sources.

Overall, these results show lenders' ability to incorporate their environmental preferences into debt contracts aligned with their incentives to manage the environmental risk of borrowers.

The findings in this study have important implications for policies to reduce pollution. Regulators refrain from imposing environmental taxes or disclosure requirements on SMEs because of the administrative burdens these initiatives impose on SMEs.[7] Instead, regulators encourage lenders to manage borrowers' environmental risk exposure, regardless of firm size. Despite this significant environmental impact and the role that lenders are expected to play in monitoring SMEs' pollution, this is the first study to investigate whether lenders incorporate meaningful information about private SMEs' environmental activities into lending decisions.

The remainder of the paper is structured as follows. Section 2 describes waste and the institutional setting. Section 3 presents the data and key measures. Section 4 presents the empirical results, and section 5 concludes.

2 Institutional setting

2.1 Waste

I use data on firms' industrial waste generation in Denmark from 2011 to 2021 to estimate SMEs' environmental impact. To date, little is known about firm-level waste production, despite waste's negative externalities, media attention, and regulators' interest in limiting waste pollution. Themelis and Ulloa (2007) estimate that solid waste landfills emit about 68 billion cubic meters, equivalent to 1.2 billion tons of CO2, of uncaptured methane gas globally.[8] Kaza et al. (2018) estimate a comparable amount—about 1.6 billion tons of CO2 equivalent emissions in 2016 or 3.11 percent of total global greenhouse emissions.[9] However,

[7]EU regulators strongly favor reducing the reporting requirements of smaller firms. See the EU Commission's communication of the SME relief package https://single-market-economy.ec.europa.eu/document/download/8b64cc33-b9d9-4a73-b470-8fae8a59dba5_en?filename=COM_2023_535_1_EN_ACT_part1_v12.pdf.

[8]See https://www.epa.gov/ghgemissions/overview-greenhouse-gases for conversions.

[9]See https://ourworldindata.org/greenhouse-gas-emissions for total greenhouse emissions.

these measures do not account for the carbon emissions from producing virgin materials, the loss of biodiversity, and other externalities. In the waste management literature, studies often include acidification of bodies of water, nutrient enrichment that harms ecosystems, ozone depletion, and the build-up of hazardous gasses in the atmosphere, microplastic in our bodies, and plastic debris in the oceans as negative environmental externalities (Cozar et al., 2014; Rillig and Lehmann, 2020).[10] These environmental externalities make waste an ideal activity for understanding firms' environmental performance.

Only a few studies investigate firms' waste. These studies focus on specialized industries, production plants, or specific substances, such as nuclear, water, or hazardous waste. In a recent study, Choy et al. (2024) investigate debt covenants tied to toxic chemicals of U.S. production facilities and find that public enforcement increases lenders' monitoring of firms' environmental activities. Using the same setting, Hsu et al. (2023) find that firms with higher toxic emissions outperform less-polluting firms and generate higher alphas. Chen et al. (2018) show that mandatory CSR reporting reduces the amount of firm wastewater and SO2 emissions. Focusing on the nuclear energy industry, D'Souza et al. (2000) find that disclosed decommissioning costs for nuclear operations are more value-relevant for riskier firms. Overall, these studies highlight the importance of waste on capital market outcomes in subsets of industries. While the number of studies in this field is limited, likely due to a lack of reliable data, industrial waste pertains to a wide range of industries, types of waste, and disposal methods.

2.2 The Danish setting

This study makes use of the setting of SMEs in Denmark, which offers several advantages. First, the data includes detailed information about firms' waste classification, treatment, and weight, as well as identifying information with respect to the firm facility, waste collector, and the receiving firm. This allows for an account of material-specific externalities and waste

[10] See, for instance, Zhao et al. (2011).

treatment options not previously investigated for smaller firms but relevant to environmental impact.

Second, the data stems from third-party waste collectors who report information about collected waste to the DEPA, and has historically been used for municipality- and country-wide waste reporting and planning, meaning that firm-level information about waste production is proprietary to the third-party collectors, the government, and the individual firms themselves unless they voluntarily disclose the data.[11] Given the closely held nature of this data, I expect customer preferences and the risk of public backlash to be less salient in this setting.

A third advantage of this setting is that it mitigates bias concerns related to managers' discretion. Greenwashing—the practice of publicly exaggerating environmental performance—is increasingly common due to the importance of environmental concerns to stakeholders, the difficulties of measuring and validating environmental outcomes, and the lack of strict disclosure standards (Wu et al., 2020). Thus, environmental data is often viewed with skepticism. In contrast, the Danish waste data used in this study are reported by third-party collectors with no incentive to misreport, and, in fact, face fines and other penalties if they report late or incorrectly. Municipalities require waste collectors to follow the filing rules, but the resource allocation to monitoring and enforcement varies across municipalities. Although some municipalities may exhibit low enforcement, Liang and Renneboog (2017) find that the national legal origin structure is the most important factor in determining ESG ratings, with Scandinavian firms achieving the highest scores.[12] To further ensure data quality, the DEPA performs checks using robust statistical methods (e.g., correcting for incorrect outliers and other irregularities).

Beyond data quality, Denmark has a strict regulatory structure. The government requires

[11] According to disclosure theory and the unraveling mechanism, firms should, in equilibrium, voluntarily disclose until the point where the value of disclosing is twice the disclosure costs (see Milgrom, 1981).

[12] Though Scandinavian firms score highest on ESG ratings, it is unlikely that all municipalities have strict monitoring and enforcement of the reporting of third-party waste collectors. Denmark has 98 municipalities with an average population of around 58,000 people, and those populations range from 1,847 to 579,366.

firms to justify and test the waste disposed in landfills and taxes landfill disposal DKK 475 (USD 70) per metric ton and incineration DKK 151 (USD 22) per metric ton, depending on the energy use and year.[13] Such taxes mean higher incentives to reduce incinerated and landfill waste.

3 Data and measures

3.1 Data selection

Table 1 tabulates the selection process. The initial data consists of financial statements for fiscal years between 2011 and 2021 with available data on full-time equivalent employees (FTEs). I exclude firms consolidated with parent companies from the initial sample. Further, because all limited liability entities in Denmark must file financial statements with the Danish Business Authority, the sample is inclusive of these firms, whereas other ESG studies are generally limited to large firms with environmental disclosures.

To identify SMEs, I restrict the sample to firms below the EU threshold for this classification. The EU defines SMEs as firms with fewer than 250 employees and up to EUR 50 million in revenue or up to EUR 43 million in total assets. Danish GAAP exempts firms from reporting revenue, cost of goods sold, and nonsalary SG&A costs, and thus I cannot control for these financial variables across the full sample. Instead, I replace the condition of EUR 50 million or less in turnover with gross profit to filter for qualified SMEs.[14] As a lower bound, I remove firms with fewer than two FTEs. These firms are likely freelancers

[13]The tax on energy recovery of waste depends on several aspects, including whether the energy is used for electricity generation or heat, the year, and the energy density of the incinerated waste. As a baseline, the Danish Tax Authority tax firms based on the gigajoule of energy generated from waste incineration. The lower bound tax of DKK 151 per metric ton of waste is calculated assuming 8 gigajoules (GJ) of energy per ton of waste and the lowest tax level between 2011 and 2021 is DKK 18.9 per GJ in 2015. Moreover, the waste incineration facilities also pay a carbon tax linked to their carbon allowances. By-products of the incineration include bottom or fly ash, which may entail additional taxes if disposed of in landfills.

[14]See https://single-market-economy.ec.europa.eu/smes/sme-definition_en. I apply a constant EUR/DKK conversion of EUR 1 = DKK 7.45 for the SME definition thresholds throughout the sample period as the Danish Crown is pegged to the Euro.

and lenders typically bundle the products and credit assessment together with the household finances of the owners. The lower-bound restriction also removes inactive, shell, and holding companies.

Waste data is assessed with the calendar year. To align this data with firms' financial statements, I exclude all firms with a reporting end date ± within 15 days of the calendar year-end and financial statements that do not cover 12 months. I then exclude public firms, as these are subject to specific reporting requirements and increased stakeholder pressure. I further restrict firms from the financial or waste management industries as they may have distinct incentives related to the production of waste than other firms.

To construct the main variables, I first remove all firm years without waste data. There are several reasons for firms to lack waste data. First, waste production is recorded in a similar manner to scope 1 greenhouse gas emissions, where only firms that control the waste are included. For instance, a firm may outsource its corporate kitchen to a third party that is then responsible and denoted as the waste producer. Alternatively, a firm may rent office space from a management firm that is responsible for all office-related waste. Second, firms operating out of private homes, holding companies, and firms without production may have no waste. Third, firms may produce little waste because collectors operate in bulk to cover multiple loads across office hotels, small firms, and households. Municipalities allow firms to hire municipality waste management services if the composition and quantities are similar to that of a standard household. Finally, I remove observations without data for common controls used across model specifications and any singletons within year-industry and year-municipality groups (Breuer and DeHaan, 2024) as these represent my main fixed effect specification.

The final sample consists of 129,375 firm-year observations across 26,652 firms, returning an average of 4.9 firm-year observations per firm. The number of firm-year observations per firm is comparable to that of the initial sample and the sample before removing SMEs without waste data.

3.2 Measures

3.2.1 Waste measures

To measure the environmental impact of waste, I follow the literature on environmental outcomes and scale the weight of waste, using total assets as a proxy for firms' operations size to obtain SMEs' waste intensity (see e.g., Ilhan et al., Ilhan et al. (2021)).[15] Following Savov (2011), I implicitly assume that weight reflects a monetary value as I scale a physical measure by a financial statement measure, such as total assets, to create a comparable metric across firms.[16]

Unlike CO2 equivalent emissions, waste intensity represents different externalities across waste substances, treatment types, and purity (see section 2.1). In order to better capture the externalities of waste, I calculate the waste intensities across three categories. First, I separate waste by its treatment type and calculate the waste intensity of recycled, incinerated, and disposed waste. Recycled waste represents the least environmentally harmful activity, consistent with the waste management literature and ESG disclosures. I follow the definitions of the EU Waste Framework and the structure of ESG disclosures when classifying recycled waste as by-products recovered for either reuse or recycling. Incineration covers waste treatment for energy recovery, and disposal is landfill waste.[17]

Second, I calculate intensity according to hazardous and nonhazardous waste categories. Hazardous waste covers substances that pose severe human or environmental danger, such as toxic, reactive, ignitable, infectious, and corrosive materials.[18] The classification of hazardous wastes is linked to the type of waste. To classify hazardous waste, I follow the European

[15] This approach is similar to waste measures in environmental disclosures of larger firms. Although they do not explicitly scale waste weight by size, in many cases, firms add production or sales levels as scaling measures in connection with environmental data. I use total assets to scale waste in the main specifications and then perform robustness checks using employees. I cannot apply revenue in my setting as Danish firms are exempt from disclosing the revenue in financial statements.

[16] I do not correct for inflation as all specifications include some variation of year fixed effects.

[17] See annexes I and II of the directive at https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:02008L0098-20180705 for descriptions of recovery and disposal types. All "R" treatment codes except "R1" represent recycling. R1 is incineration, and all D codes are disposal.

[18] See annex III of the directive at https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:02008L0098-20180705

Waste Catalogue (EWC) codes, which include 842 types of waste material, and, in many cases, the process from which the waste is derived.[19] The EU marks hazardous EWC codes with an asterisk, and waste collectors register the EWC codes of waste when reporting to DEPA.

Third, I calculate waste intensity according to sorted and unsorted waste categories. The DEPA also requires collectors to classify waste according to a local Danish waste system. This system includes 45 categories of which five categories represent residual waste fractions when waste collectors cannot precisely place the waste in other categories. I use these categories to determine whether SMEs sort their waste.[20]

Table 2 shows the average weight of waste scaled by assets (DKK '000) across industries and over the sample period.[21] I follow the industry classification of the Danish Business Authority and report the scaled waste production across the upper single-letter (Level 1) NACE industry categories.[22] The left side of the table shows that the construction industry (F) has the highest waste intensity, followed by transporting and storage (H) and administrative and support companies (N, i.e., leasing companies). Electricity, gas, steam and air conditioning supply (D), information and communication (J), and human health and social work (Q) have the lowest waste production scaled by assets. Manufacturing, surprisingly, produces only 4.97 kilograms per DKK 1,000 assets. This may reveal the industry's focus on resource efficiency or a high level of assets. The most frequent industries in the sample are wholesale and retail, manufacturing, and construction. The right side of the table reveals that the number of observations and the average waste intensity increase over the sample

[19] See https://eur-lex.europa.eu/eli/dec/2014/955/oj for EWC codes. The DEPA adds one additional EWC code to account for Danish regulation on asbestos waste.

[20] Unsorted waste includes fractions E3, E4, E24, E26, and E27 of the DEPA waste classification system. A list in Danish is available at https://mst.dk/media/g1znqdtv/bilag_a_vaerdikodeliste_308_2023.xlsx.

[21] Conversion rates are 6.23 (0.161) USD/DKK (DKK/USD), using the average exchange rate between 2010 through 2022.

[22] See https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF for an overview of the industry categories. I use the second version of the classification codes across the full sample. The industry classification follows a tree structure. I later use the industry codes at the two-digit level for industry fixed effects.

period, with an average waste production scaled by assets of 7.28 kilograms based on 8,866 observations in 2011 to 8.02 kilograms based on 14,608 observations in 2021.

3.2.2 Cost of debt

The main outcome variable of this study is the cost of debt. Following Minnis (2011), I calculate firms' cost of debt as financial expenses scaled by the net-interest-bearing debt (NIBD) and truncate observations 10 percentage points higher than the 10-year government bond and observations below the 5 and above the 95 percentiles.[23] NIBD is total liabilities less trade payables. This approach may include debt from sources of capital other than lenders such as contingent liabilities, tax authorities, and deferred revenue. In robustness tests, I replace NIBD with debt items directly linked to products of financial institutions.

4 Empirical results

4.1 Descriptive statistics

Table 3 shows the descriptive statistics of all main variables after winsorization. Firms generate about 88 tons of waste on average, while the median is around 9 tons, indicating a left-skewed distribution. The mean (median) waste intensity is 7.76 (1.07) kilograms (kg) per DKK 1000 total assets, also indicating a left-skewed distribution. On average, around 4 kilograms per DKK 1000 assets of waste is recycled whereas firms' average incinerated and disposed waste is around 0.8 kilograms. Firms produce about 20 times nonhazardous as hazardous waste on average, and twice the amount of sorted relative to unsorted waste. Most SMEs generate no disposed or hazardous waste.

The average cost of debt is 2.83 percent, which is reasonably low due to the low-interest rate environment across the sample period. The average 10-year government bond yield is

[23]The 10-year government bond yields can be found at https://www.statistikbanken.dk/statbank5a/default.asp?w=2560 and average yields are observed every quarter across the year.

0.70 percent from 2011 to 2021. Sample firms are on average about 17 years (201 months) old.

Table 4 shows Pearson and Spearman correlations between the cost of debt, waste measures, and size. Two key observations emerge from the correlations. First, the cost of debt correlates significantly with most of the waste measures. Second, the waste intensity (3) is highly correlated with the three intensity measures representing better environmental performance: Recycled (4), nonhazardous (7), and sorted (9) as these constitute the majority of waste.

4.2 Lenders' debt pricing of SMEs' pollution

To investigate whether and how lenders price SMEs' environmental performance into debt, I test the association between the firms' waste intensity and their cost of debt. Lenders have several options when structuring debt contracts with smaller firms, and the cost of debt constitutes a key factor in credit agreements. It allows lenders to adjust for information asymmetry and risks to maximize benefits when other contractual terms (e.g., collateral and contingencies) are costly to the firm or are insufficient.

Initially, I answer whether lenders do price SMEs' pollution. I expect lenders to incorporate smaller firms' environmental performance into their cost of debt because of lenders' financial incentives to adjust lending rates for the borrowers' environmental risk exposure and to offer green financing products (see footnote 4). However, the incentive to manage sustainability risk is influenced by environmental <u>impact</u> and not by environmental <u>improvements</u>. In addition, lenders' development of sustainability-focused products requires them to collect information about firms' investment decisions and their environmental impact. Higher monitoring costs relative to the size of credit agreements likely attenuates lenders' motivation to monitor benefits, and thus, lenders benefit less from managing environmental risk and encouraging firm-specific environmental improvements of SMEs. Similarly, lenders' green financing products must lead to more sustainable investment decisions by firms to drive environmental change. Thus, I hypothesize lenders consider only cross-firm differences in SMEs' environmental impact and not firm-specific improvements, consistent with lenders pricing debt but through selection. I operationalize my tests by estimating equation 1 to capture whether higher SMEs' environmental performance is associated with cost of debt benefits.

$$CoD_{it} = \beta_0 + \beta_b waste_{it} + \gamma_c controls_{it-1} + \mathit{fixed\ effects} + \epsilon_{it} \tag{1}$$

where CoD is the cost of debt (in %) for firm i time t. I describe the cost of debt measure in subsection 3.2.2 and *waste* measures in subsection 3.2.1. *Controls* include the accounting-based bankruptcy model variables from Ohlson (1980) as controls for firms' credit. Regenburg and Seitz (2021) show that this model has the highest area under the ROC curve (AUC) and Pseudo R^2 in a comparable setting of private small firms. The bankruptcy model variables include total liabilities scaled by total assets (TL/TA); earnings before interest, tax, depreciation, and amortization scaled by total liabilities (EBITDA/TL); Net income scaled by total assets (NI/TA); net working capital scaled by total assets (NWC/TA); current liabilities scaled by current assets (CL/CA); an indicator of one if the sum of the net income in the last two financial statements is negative (NITWO); an indicator if total liabilities are higher than total equity (OENEG); and the change in net income scaled by the absolute mean of net income in the last two financial statements (CHIN). I also include controls for firm size, age, and complexity, which I proxy by the number of subsidiaries. I list all variable definitions in Appendix A.

I include year-industry fixed effects using the two-digit NACE industry codes to account for any industry-specific shocks or trends within a given year. Examples include waste management, operation, and product innovations which affect either the credit risk of firms, their waste management practices, or both. Year-industry effects also control for industry-specific changes in regulations. Considering year and industry effects is similar to the approach of Goss and Roberts (2011), Chava (2014), Houston and Shan (2022), and Ehlers et al.

(2022), though my approach is more robust as I control for industry effects within a given year. Kacperczyk and Peydró (2024) implement firm fixed effects to investigate the impact of lenders' carbon-neutral commitments on borrowers' interest expenses. They include no controls for firms' credit risk resulting in credit risk implications of firms' environmental performance embedded in their findings. Instead, I investigate whether lenders have preferences for SMEs with less pollution as distinct from common risk measures.

I also include year-municipality fixed effects to control for time-specific changes to local waste management regulation and enforcement, geographic location effects, and local economic conditions, including differences in the local job pool and most variation in access to waste treatment facilities. (I exploit the remaining variation later.) Other studies rely on time-invariant country effects, but these likely ignore relevant changes in local waste regulation. The fixed effect structure allows me to compare how SMEs' environmental performance is associated with the cost of debt across firms but within the same year-industry and independent of municipality variation over time. I cluster standard errors at the firm level across all specifications because the variation in treatment (e.g., waste measures) stems from firms' production of different levels of waste (Abadie et al., 2023). The main results are qualitatively similar when clustering standard errors at the year-industry and when including year, industry, and municipality fixed effects, separately.[24]

I hypothesize that lenders account for a residual component of SMEs' environmental performance into their debt pricing, which is not explained by firms' accounting information, industry, and geographical placement within a given year (i.e., $\beta_1 > 0$). The systemic environmental risk of borrowers provides lenders with the financial incentives to reduce their portfolio exposure to SMEs with more pollution, or transfer that risk through the issuance of green bonds to investors and green loans to SMEs. Table 5 presents the main results. Column 1 reveals that the waste intensity is significantly associated with SMEs' cost of debt. The coefficient is positive, indicating that lenders provide a lower cost of debt to SMEs with

[24] Firms rarely change industry and firm location. The main results are robust when assigning fixed industry and municipality indicators and removing firms that change.

less pollution. In terms of magnitude, a within-group one-standard-deviation change (=25 kg per DKK 1,000 assets) translates into a change in the cost of debt of 3.1 basis points. Coefficient estimates of control variables are untabulated for brevity, but are similar in size to the cross-section cost of debt estimation results in Regenburg and Seitz (2021) who exploit a comparable sample of private SMEs.

In the following analysis, I separate waste intensity into three waste categorizations to corroborate that lenders differentiate between different types of waste in a way that aligns with the ecological externalities of waste and concerns of alternative explanations. In column 2, I split the waste intensity into three types of waste treatment. The coefficient of recycled waste intensity is positive and highly significant. A decrease in the within-group one-standard deviation (=18 kg per DKK 1000 assets) is associated with a reduction of 2.8 basis points in the cost of debt. Moreover, the coefficients of incineration and disposal waste intensities are higher but statistically insignificant.

Next, I categorize the waste intensity by whether the waste is hazardous. Column 3 reveals that the coefficient of hazardous waste is more than ten-fold larger than that of nonhazardous waste. The difference in the coefficients is significant (p-value = 0.067). This result suggests that lenders not only incorporate SMEs' environmental impact into debt but that they also differentiate between environmental activities when considering the impact. For nonhazardous waste intensity, an increase of within-group standard deviation (=21 kg per DKK 1000 assets) is associated with an average 2.0 basis points higher cost of debt. For the hazardous waste intensity, an increase of the within-group standard deviation (=1.47 kg per DKK 1000 assets) is associated with an average 1.7 basis points higher cost of debt.

Column 4 reveals a similar interpretation when I run a separate analysis according to whether SMEs sort waste. The coefficient of unsorted waste is about 50 percent higher than that of sorted waste. SMEs experience, on average, a (1.6) 2.0 basis points lower cost of debt when their (un)sorted waste intensity decreases by (8) 16 kg per DKK 1000 assets, which represents a within-group standard deviation change. The monotonic decrease in coefficient estimates over less harmful waste intensities in columns 2 through 4 suggests that lenders reward SMEs for lower environmental impact.

One concern is that unobserved firm-specific variation explains the association between SMEs' pollution and the cost of debt. Implementing firm fixed effects alleviates the concern by removing any time-invariant firm characteristics that explain both SMEs' pollution and the cost of debt (i.e., any unobserved time-invariant confounders).[25] However, firm fixed effects also remove variation across firms. This is undesirable if lenders follow their risk management incentives focusing on the level of SMEs' environmental risk exposure.[26] Lenders would benefit from promoting firms' green transition by offering green loans regardless of their pollution level, but this only has an effect if the loans finance projects at a lower cost of debt that is otherwise not financially feasible for borrowers.

Next, I try to understand whether lenders price pollution by providing a lower cost of debt to SMEs with inherently lower pollution or whether lenders engage in SMEs' green transition, regardless of their level of pollution. This is econometrically challenging without information on individual lenders' underlying decision models. In the best efforts to gauge this, I exploit differences in fixed effect structures. Specifically, given the tight structure of industry-year and municipality-year fixed effects, adding firm-fixed effects removes firms' level of the cost of debt and waste pollution returning only variation in these within firms (Breuer and DeHaan, 2024).

Consequently, I reestimate the models in columns 1 through 4 with firm fixed effects. Columns 5 through 8 reveal the results showing no statistical significance for any of the waste intensities at conventional levels. This result indicates that lenders exhibit selection behavior. However, it is crucial to acknowledge that this methodological effort to understand how lenders price SMEs' pollution may still be prone to omitted variable bias and other endogeneity concerns if unobserved factors affecting both SMEs' pollution levels and their

[25]Firms fixed effects remove the mean level of both the dependent variable and independent variables returning within-group variation (Breuer and DeHaan, 2024).

[26]Firms' cost of debt and environmental impact may be sticky, which may also remove variation that is associated with lenders' environmental preferences.

cost of debt are not entirely addressed by the fixed effects. These results are consistent with lenders rewarding SMEs with less pollution with a lower cost of debt rather than promoting individual improvements to SMEs' environmental performance pollution.

4.2.1 Two-stage least square approach

As cautioned above, the main specifications are prone to omitted correlated variable bias if uncontrolled variation in firm-specific time-variant characteristics affects firms' cost of debt and their environmental performance (Larcker and Rusticus, 2010). To combat this concern I implement a two-stage least square approach and use waste-type specific variation in treatment facilities available to firms as an instrument variable of firms' waste intensity. Table IA.1 of the Internet Appendix shows that distance to waste treatment facility is a significant predictor of recycling across all fixed effect structures. The same applies to SMEs' waste intensity. However, SMEs' decisions about where to dispose of their waste are endogenous. Instead, the availability of waste facilities is not. After the SMEs' establishment, they most likely have little power over the supply of waste facilities and services nearby.

I formulate the measure of the availability of waste treatment facilities as follows in equation 2.

$$\Delta Waste\ facilities_{i,t} = \sum \omega_{i,t-1,p,m} dist_{t-1,p,f,m} - \sum \omega_{i,t,p,m} dist_{t,p,f,m} \tag{2}$$

where $\Delta Waste\ facilities$ is the change in the average number of waste facilities f that treat waste material m within distance $dist$ of firms' office or plant p between time t and $t-1$ for firm i. The distance is weighted by the waste amount and aggregated to a single measure per firm year.

The main specification includes year-industry and year-municipality fixed effects, meaning that I estimate values of total waste intensity based on the variation in waste-type specific access to treatment facilities across firms geographically within the same municipality while controlling for time-variant industry effects. I use a distance of 50 kilometers (∼31 miles) as this is approximately the largest distance between any point within a municipality and the main city of that municipality. Thus, the variation arises from differences in SMEs' location within municipalities and treatment facilities, predominantly placed outside SMEs' municipalities.

In addition, if changes in access to a waste facility affect firms' waste generation, the effect may also affect their operations and financial situation if the accessibility imposes higher costs. Estimating the return on assets (as a proxy for profitability) reveals that if anything SMEs the changes in available waste treatment facilities are positively associated with profitability. This result is contrary to the access to fewer waste facilities imposing higher costs, and through this channel, affecting SMEs' cost of debt. Based on these institutional observations, the instrument qualitatively fulfills the relevance criteria and exclusion restriction, despite no instruments being perfect Larcker and Rusticus (2010). In addition, I use lagged controls and, thus, do not face issues with mediating control variables (Gow et al., 2016).

I calculate the Wu-Hausman F-statistic and the individual F-test to examine whether the instrument is weak. Both are significantly different from zero indicating that the instrument explains a meaningful part of the variation in total waste intensity. In contrast, the within adjusted R^2 is low. However, not all SMEs in the sample experience changes in access to treatment facilities.

The model is unlikely to be over-identified as I use a single instrument on a fixed effect model. A single instrument likely cannot exceed the number of endogenous variables. For completeness, I include the Sargan test statistic and the probability value to assess the over-identifying restrictions formally. The χ^2 test statistic is less than 0.0001 and the p-value is virtually equal to one, meaning that the over-identifying restrictions test fails to reject the appropriateness of the instruments.

Table 6 presents the results. Column 1 shows the first stage estimation of total waste intensity. Here, the coefficient of $\Delta Waste\ facilities$ shows that when one more facility within 50 kilometers accepts SMEs' waste types they produce on average 0.3 kilograms more waste per DKK 1000 assets. The second stage results in column 2 show that the instrument waste intensity significantly predicts the cost of debt. The coefficient is about 18 times higher than the main result in table 5. However, the within-group one-standard deviation is 1.91 kilograms per DKK 1000 which translates into a 4.0 basis points effect on the cost of debt. This magnitude is comparable to the 3.1 basis points effect of the main results, alleviating endogeneity concerns.

I obtain similar inferences using the absolute number of available treatment facilities (untabulated), but, in that case, the instrument includes firms' initial and possibly endogenous decision to locate near waste treatment facilities. Overall, these results indicate that SMEs' waste pollution causally affects their cost of debt.

4.2.2 Waste materials

In section IA.1.1 of the Internet Appendix, I empirically show that the composition of firms' waste materials explains most of the variation in their recycling. That is because technological advances, material characteristics, and local conditions determine the possibility of recycling certain materials (see e.g., Hopewell et al., 2009; Pires et al., 2011; and Ragaert et al., 2017). In IA.1.2 of the Internet Appendix, I reestimate the main results controlling for firms' waste composition (i.e., the types of waste they produce) to alleviate concerns that differences in characteristics across waste types drive the results. I find qualitatively similar but attenuated results in these estimations as they remove variation across waste types.

4.2.3 Robustness tests

Alternative cost of debt measure: I scale financial expenses by total liabilities less accounts payable when measuring the cost of debt (see the definition for cost of debt in table A.1 of Appendix A. However, one concern is that liabilities include tax and contingent liabilities that would increase with waste intensity. This could occur, for example, in the case of legal claims against SMEs' illicit waste handling. To mitigate this concern, I reestimate the main results using an alternative denominator of financial expenses. Specifically, I include only items of debt that unequivocally derive from financial institutions as the denominator. I provide the results in section IA.2.1 of the Internet Appendix. The results are largely qualitatively similar with some smaller inconsistencies.

Alternative waste intensity measures: I scale waste by total assets to obtain intensities in the main specifications. Concerns may arise if waste and total assets correlate highly and small changes in total assets drive the results. To alleviate this concern, I reestimate the main results using SMEs' FTEs. I present the results in section IA.2.2 of the Internet Appendix and find results qualitatively similar to the main findings.

4.2.4 New debt

Debt contracting and lenders' acquisition of private information on firms' business activities allow lenders to incorporate their preferences for managing risk, including risks related to firms' environmental impact (e.g., Jensen and Meckling, 1976). As a potential market solution, lenders offer financing products that contractually require borrowers to use the credit on investments that improve their environmental performance.[27] Lenders may subsequently exploit their financial intermediation role and bundle credit agreements into bonds by labeling them green and selling them to third-party investors with preferences for lower environmental risk exposure. In addition, lenders may incorporate environmental covenants into loan agreements, requiring firms to adhere to specific environmental standards, practices, or performance targets that mitigate environmental risks even further (Chava, 2014). Lenders' contracting, thus, makes their provision of debt to SMEs an ideal activity to incorporate their environmental preferences.

[27] See footnote 4.

Using the event of SMEs obtaining new debt, I investigate whether lenders place more emphasis on these firms' environmental impact. Table 7 reveals the results. Column 1 shows the marginal effect of SMEs' obtaining new debt on lenders' pricing of firms' pollution. Specifically, I interact the waste intensity in equation 1 with the timing of SMEs' obtaining new debt. I apply the definition of new debt from Naranjo et al. (2022) and set an indicator of one when the change in long-term liabilities from time $t-1$ to $t+1$ normalized by total assets at time $t-1$ increases by more than 5 percent. The coefficient of the interaction between waste intensity and new debt is 0.0017, indicating that lenders price SMEs' pollution higher when providing credit. This result is consistent with lenders offering financing products tied to firms' investment in better environmental performance.

In column 2, I reestimate column 1 using an alternative definition of new debt. Here, I restrict changes in debt to liabilities directly linked to the lending activities of financial institutions, similar to the definition of net interest-bearing debt in section IA.2.1 of the Internet Appendix. This definition includes the short- and long-term parts of bank loans, mortgages, and other debt obligations. I observe less variation in SMEs' new debt financing using the alternative definition as fewer SMEs report these items. The coefficient of the interaction between waste intensity and new debt continues to be statistically significant at conventional levels.

In column 3, I replace the indicator of new debt with an indicator of SMEs obtaining new equity as a placebo test. Naranjo et al. (2022) also defines new equity. Specifically, I set an indicator of new equity to one when equity from time $t-1$ to $t+1$ less net income of time t and $t+1$ scaled by total assets at time $t-1$. The coefficient of the interaction between waste intensity and new equity is insignificant and close to zero, consistent with lenders not obtaining new information when firms raise new equity capital. Collectively, these results are consistent with debt offering an opportunity for lenders to incorporate their preferences for better environmental performance into debt pricing.

5 Conclusion

This paper provides evidence on whether and how lenders exhibit environmental preferences when pricing SMEs' debt. Lenders have superior abilities to collect information and monitor firms' sustainability activities. This allows lenders to intermediate environmental risk and promote firms' investments in reducing pollution. However, incorporating firms' environmental performance into debt pricing may be proportionately more costly for smaller firms as they have limited information available and often face no public scrutiny of their environmental activities. This raises the question of whether lenders exercise their financial incentives to manage and intermediate SMEs' environmental risk and promote the green transition.

Using unique data on firms' waste generation and treatment in Denmark from 2011 to 2021 to proxy for their environmental performance, I show that SMEs with less waste pollution are associated with a lower cost of debt. Lenders incorporate their environmental preferences consistently across different environmental activities. When separating SMEs' waste by its harmfulness to the environment, I find that the association between environmental performance and cost of debt is stronger for more harmful categories of waste. In addition, lenders' pricing of SMEs' pollution is robust to a 2SLS approach using changes in SMEs' access to waste facilities as an instrument. This indicates that endogeneity concerns such as omitted variable bias do not explain the main findings. In additional analyses, I test the relation between SMEs' pollution and the cost of debt when SMEs obtain new debt. Consistent with lenders' offering of products linked to environmental risks, I show that lenders' emphasis on SMEs' pollution increases when providing new debt.

I also provide results consistent with lenders offering a lower cost of debt to SMEs with less pollution (i.e., through selection), rather than supporting reductions in SMEs' environmental impact when not financially advantageous to these firms. However, this interpretation is prone to endogeneity and econometric challenges.

The main contribution of the paper is to show that lenders impose environmental preferences through selection on a set of firms without apparent transparency or public scrutiny related to their operations. This adds first to the literature on lenders' monitoring role by showing that lenders can obtain relevant information to evaluate firms' environmental performance in settings with limited information availability,[28] and second, to the literature on lenders' preferences for environmentally responsible firms[29]. Finally, the findings of this study have implications for regulators' efforts to reduce the environmental impact of SMEs. To my knowledge—no evidence exists on whether lenders can incorporate SMEs' environmental activities into lending decisions. Despite this, the ECB does pressure lenders to manage the environmental risks of borrowers across all firm sizes.

[28]E.g., studies show that lenders incorporate environmental considerations into lending decisions of larger or public firms (Amiram et al., 2023; Choy et al., 2024; Lee and Zakota, 2024)

[29]E.g., Sharfman and Fernando (2008) and Chava (2014). This is consistent with Amiraslani et al. (2023), Houston and Shan (2022), and Walz (2022) on investors' environmental preferences, and Kacperczyk and Peydró (2024) lenders' selection of borrowers' with less pollution.

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Appendix A Variable definitions

Table A.1: Variables definitions

Variable name	Definition
Waste measures	
Waste	The weight of total waste production in kilograms of a given firm within a given year.
Waste/TA	Waste scaled by total assets in DKK thousands.
Recycled/TA	The total weight in kilograms of firms' waste within treatment code R2 through R15 of the EU Waste Directive 2008/98/EC scaled by total assets in DKK thousands.
Nonrecycled/TA	The total weight in kilograms of firms' waste within treatment code R1 and D1 through D15 of the EU Waste Directive 2008/98/EC scaled by total assets in DKK thousands.
Incinerated/TA	The total weight in kilograms of firms' waste within treatment code R1 through R15 of the EU Waste Directive 2008/98/EC scaled by total assets in DKK thousands.
Diposed/TA	The total weight in kilograms of firms' waste within treatment code D1 through D15 of the EU Waste Directive 2008/98/EC scaled by total assets in DKK thousands.
Nonhazardous/TA	The total weight of waste classified as nonhazardous according to the EU Waste Directive 2008/98/EC scaled by total assets in DKK thousands.
Hazardous/TA	The total weight of waste classified as hazardous according to the EU Waste Directive 2008/98/EC scaled by total assets in DKK thousands.
Sorted/TA	The total weight in kilograms of industrial waste not in code E03, E04, E24, E26, and E27 of the Danish Environmental Protection Agency waste category system scaled by total assets in DKK thousands.
Unsorted/TA	The total weight in kilograms of industrial waste in code E03, E04, E24, E26, and E27 of the Danish Environmental Protection Agency waste category system scaled by total assets in DKK thousands.
Lending variables	
Cost of debt	Cost of debt is financial expenses divided by the average of net interest-bearing debt ($NIBD$), which is equal to total liabilities less account payables for $t-1$ and t. $CoD = \frac{FinExp}{(NIBD_{t+1} + NIBD_t)}$ where $NIDB = Total\ liabilities - Account\ payables$ I follow Minnis (2011) and truncate cost of debt at the 5 and 95 percentiles and remove all observations 10 percentage points above the yield of the Danish 10-year government bond.

Variable name	Definition
New debt	New debt is the debt part of the new finance measures calculated as $New\ debt_t =$ $$\begin{cases} 1, & \dfrac{LTD_{t+1} - LTD_{t-1}}{TA_{t-1}} > 0.05 \\ 0, & Otherwise \end{cases}$$ where $LTD = long\ term\ debt$ following Naranjo et al. (2022) and also used in Godsell et al. (2017)
New equity	New equity is defined as $New\ equity_t =$ $$\begin{cases} 1, & \dfrac{E_{t+1} - (E_{t-1} + NI_{t+1} + NI_t)}{TA_{t-1}} > 0.05 \\ 0, & Otherwise \end{cases}$$ where $E = equity$ and $NI = net\ income$ following Naranjo et al. (2022) and also used in Godsell et al. (2017)
Common controls	
Age	The natural logarithm of age measured in months since registration date with the Danish Business Authorities.
Log(TA)	The natural logarithm of total assets in thousands.
Subsidiaries	The inverse hyperbolic sine of the number of subsidiaries.
Ohlson (1980) control measures	
NI/TA	Net income scaled by the beginning of period total assets, $\dfrac{NI}{TA_{t-1}}$
NWC/TA	Net working capital scaled by total assets, $\dfrac{NWC_t}{TA_t}$ $NWC_t = WCA_t - WCL_t$ WCA=Working Capital Assets =Current Assets -cash and cash equivalents -properties held for sale -receivables from closely related parties WCL=Working Capital Liabilities =current liabilities -current part of mortgage -current part of bank debt -liabilities to closely related parties -dividends if included in current liabilities
RE/TA	Retained earnings scaled by total assets, $\dfrac{RE_t}{TA_t}$

Variable name	Definition
BVE/TL	Book value of equity scaled by total liabilities, $\frac{BVE_t}{TL_t}$
GP/TA	Gross profit scaled by total assets at time $t-1$, $\frac{GP_t}{TA_{t-1}}$
TL/TA	Leverage. Total liabilities scaled by total assets, $\frac{TL_t}{TA_t}$
$EBITDA/TL$	Earnings before interest, tax, depreciation, and amortization scaled by total liabilities, $\frac{EBITDA_t}{TL_t}$
CL/CA	Current ratio. Current liabilities scaled by current assets, $\frac{CL_t}{CA_t}$
$NITWO$	An indicator variable that set to one if the sum of the last two years' earnings is negative and zero otherwise, $NITWO = \begin{cases} 1, & Net\ income_{t-1} + Net\ income_t < 0 \\ 0, & Otherwise. \end{cases}$
$OENEG$	An indicator set to one if owners' equity is negative and zero otherwise, $OENEG = \begin{cases} 1, & Total\ liabilities_t > Total\ assets_t \\ 0, & Otherwise. \end{cases}$
$CHIN$	The change in net income scaled by the sum of the absolute net income at time t and $t-1$, $Chin = \frac{\Delta Net\ income_t}{\lvert Net\ income_{t-1}\rvert + \lvert Net\ income_t\rvert}$

Tables

Table 1: Sample selection

Step	Filter	Observations: Firm-years	Observations: Firms	Dropped: Firm-years	Dropped: Firms
1	Initial sample	653,501	123,284		
2	Keep SMEs with two or more FTEs	343,931	65,557	309,570	57,727
3	Remove firms without calendar-end fiscal year and 12 months	343,898	65,552	33	5
4	Remove listed firms	343,844	65,537	54	15
5	Remove financials	336,226	63,759	7,618	1,778
6	Remove waste management firms	330,922	63,075	5,304	684
7	Remove observations without waste data	167,404	33,313	163,518	29,762
8	Remove singletons and observations without data for controls	129,375	26,652	38,029	6,661

This table presents the filtration process of the data sample. (1) The initial sample is financial statements from Experian (augmented with statements from Orbis) from 2011 to 2021 that has eligible data on full-time equivalent employees and total assets. (2) I keep SMEs with two or more full-time equivalent (FTE) employees following the EU's definition of Small- and Medium-sized Enterprise of less than 250 FTE and either lower than EUR (DKK) 50 (372,9) million in gross profits or 43 (319,8) million in total assets. I use gross profits instead of revenue as Danish firms are exempt from reporting revenue. (3) I keep all firms following the calendar year-end and covering 12 months. I then remove (4) listed firms, (5) firms in the financial industry, and (6) the waste management industry as the environmental activities of these firms face alternate scrutiny. In step (7), I remove firms without waste data. Last (8), I remove observations without data for controls and singletons within year-industry and year-municipality groups following Breuer and DeHaan (2024).

Table 2: Avg. waste/TA across industries and over time

NACE codes Id	Name	Avg. kg/TA	Obs.	Year	Avg. kg/TA	Obs.
A	Agriculture, forestry and fishing	4.56	3,183	2011	7.27	8,866
B	Mining and quarrying	2.13	220	2012	7.18	9,774
C	Manufacturing	4.97	22,299	2013	7.35	10,202
D	Electricity, gas, steam and air conditioning supply	0.58	218	2014	7.58	11,123
F	Construction	19.67	24,485	2015	7.80	11,330
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	2.76	40,130	2016	7.89	11,617
H	Transporting and storage	19.65	5,453	2017	8.00	12,078
I	Accommodation and food service activities	7.05	9,709	2018	7.90	12,487
J	Information and communication	0.63	3,126	2019	7.89	13,135
L	Real estate activities	1.85	2,822	2020	8.03	14,155
M	Professional, scientific and technical activities	2.45	6,954	2021	8.02	14,608
N	Administrative and support service activities	16.22	4,638			
O	Public administration and defense; compulsory social security	1.65	19			
P	Education	1.02	450			
Q	Human health and social work activities	0.61	3,063			
R	Arts, entertainment and recreation	3.95	1,366			
S	Other services activities	2.08	1,236			
U	Activities of extraterritorial organizations and bodies	2.59	4			
		7.76	129,375		7.76	129,375

This table shows the average weight of waste in kilograms per DKK 1,000 total assets and the number of firm-year observations across industries and time. NACE industry codes are defined at the single-letter categories. Total assets (the denominator) are not adjusted for inflation.

Table 3: Descriptive statistics

	Obs.	Mean	StdDev	P5	P25	Median	P75	P95
Waste measures$_t$								
Waste (in kilograms)	129,375	87,772	324,342	255	2,420	9,020	33,743	346,739
Waste/TA	129,375	7.76	28.05	0.02	0.28	1.07	3.86	26.88
Recycled/TA	129,375	5.15	20.02	0.00	0.05	0.42	2.03	18.49
Incinerated/TA	129,375	0.83	2.23	0.00	0.00	0.03	0.54	4.43
Disposed/TA	129,375	0.74	3.48	0.00	0.00	0.00	0.01	2.93
Nonhazardous/TA	129,375	6.68	24.13	0.00	0.22	0.89	3.30	23.63
Hazardous/TA	129,375	0.34	1.59	0.00	0.00	0.00	0.02	1.28
Sorted/TA	129,375	4.18	17.25	0.00	0.03	0.34	1.63	13.53
Unsorted/TA	129,375	2.84	9.05	0.00	0.00	0.29	1.38	13.16
Cost of debt$_t$ (in %)	129,375	2.83	2.04	0.32	1.22	2.41	4.00	6.91
Controls$_{t-1}$								
Age (months)	129,375	201.07	171.93	39	90	153	258	497
Total assets	129,375	37,098	192,026	1,051	3,163	7,692	22,239	127,784
Subsidiaries	129,375	0.14	0.66	0	0	0	0	1
TL/TA	129,375	0.68	0.32	0.25	0.49	0.66	0.82	1.17
EBITDA/TL	129,375	0.12	0.38	-0.36	-0.05	0.06	0.24	0.82
NWC/TA	129,375	0.12	0.30	-0.37	-0.05	0.12	0.33	0.61
CL/CA	129,375	1.05	1.17	0.27	0.54	0.76	1.06	2.76
NI/TA	129,375	0.06	0.16	-0.19	0.00	0.05	0.13	0.30
NITWO	129,375	0.22	0.42	0	0	0	0	1
OENEG	129,375	0.08	0.27	0	0	0	0	1
CHIN	129,375	0.02	0.61	-1.00	-0.37	0.04	0.43	1.00
Firm-year obs.	26,652	4.85	3.48	1	2	4	8	11

This table shows descriptive statistics. All variables are defined in table A.1 of Appendix A, cost of debt follows the construct of Minnis (2011), and all other continuous variables are winsorized at the 1% and 99% levels. The last row presents summary statistics for the number of firm-year observations per firm where obs. represents the number of unique firms in the main sample.

Table 4: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Cost of debt		**0.03**	**0.05**	**0.03**	**0.02**	**0.06**	**0.05**	**0.03**	**0.05**	**0.02**	**-0.03**
(2)	Waste	**-0.01**		**0.73**	**0.64**	**0.32**	**0.36**	**0.70**	**0.33**	**0.60**	**0.53**	**0.35**
(3)	Waste/TA	**0.02**	**0.72**		**0.76**	**0.36**	**0.31**	**0.96**	**0.22**	**0.69**	**0.68**	**-0.32**
(4)	Recycled/TA	**0.01**	**0.68**	**0.93**		**0.03**	**0.14**	**0.74**	**0.26**	**0.81**	**0.36**	**-0.13**
(5)	Incinerated/TA	**0.01**	**0.14**	**0.25**	**0.16**		**-0.04**	**0.38**	**0.07**	**0.11**	**0.51**	**-0.05**
(6)	Disposed/TA	**0.02**	**0.45**	**0.58**	**0.40**	**0.10**		**0.26**	**0.35**	**0.21**	**0.31**	**0.08**
(7)	Nonhazardous/TA	**0.01**	**0.70**	**0.98**	**0.93**	**0.26**	**0.55**		**0.10**	**0.65**	**0.69**	**-0.30**
(8)	Hazardous/TA	0.01	**0.42**	**0.52**	**0.46**	**0.13**	**0.51**	**0.43**		**0.32**	**0.09**	**0.15**
(9)	Sorted/TA	**0.02**	**0.71**	**0.92**	**0.86**	**0.15**	**0.54**	**0.89**	**0.50**		**0.17**	**-0.09**
(10)	Unsorted/TA	**0.01**	**0.48**	**0.76**	**0.73**	**0.41**	**0.49**	**0.77**	**0.41**	**0.52**		**-0.19**
(11)	Size	**-0.06**	**0.20**	**-0.10**	**-0.08**	**-0.22**	**-0.08**	**-0.10**	**-0.06**	**-0.06**	**-0.17**	

This table shows the correlation matrix of the main variables and control variables for the bankruptcy, cost of debt, and capital demand tests. The lower-left corner is Pearson correlations, and the upper-right corner shows Spearman rank correlations. All variables are defined in table A.1 of Appendix A, cost of debt follows the construct of Minnis (2011), and all other continuous variables are winsorized at the 1% and 99% levels. Correlations in bold are significant at the 5% level.

Table 5: Lenders' pricing of SMEs' pollution

Dep = Cost of debt_t	Across firms				Within firms			
	(1) Total	(2) Treatment	(3) Hazard	(4) Sorted	(5) Total	(6) Treatment	(7) Hazard	(8) Sorted
Waste/TA_t	0.0012***				0.0002			
	(0.0004)				(0.0003)			
Recycled/TA_t		0.0015***				0.0003		
		(0.0005)				(0.0005)		
Incineration/TA_t		0.0028				-0.0002		
		(0.0043)				(0.0037)		
Disposal/TA_t		0.0026				0.0017		
		(0.0026)				(0.0022)		
Nonhazardous/TA_t			0.0009**				0.0001	
			(0.0004)				(0.0004)	
Hazardous/TA_t			0.0112**				0.0057	
			(0.0055)				(0.0042)	
Sorted/TA_t				0.0012**				-0.0003
				(0.0006)				(0.0005)
Unsorted/TA_t				0.0019*				0.0013
				(0.0011)				(0.0010)
Controls_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects								
Year-Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	No	No	No	No	Yes	Yes	Yes	Yes
Observations	129,375	129,375	129,375	129,375	129,375	129,375	129,375	129,375
Without singletons	129,375	129,375	129,375	129,375	125,539	125,539	125,539	125,539
Adj. R^2	0.17	0.17	0.17	0.17	0.62	0.62	0.62	0.62
Within Adj. R^2	0.08	0.08	0.08	0.08	0.02	0.02	0.02	0.02

This table provides estimation results for equation 1. All estimations include year-industry fixed at the two-digit NACE industry code and year-municipality fixed effects. Columns 5 through 8 also include firm fixed effects. Standard errors are clustered at the firm level and shown in parentheses. All variables are defined in table A.1 of Appendix A, cost of debt follows the construct of Minnis (2011), and all other continuous variables are winsorized at the 1% and 99% levels. ***, **, and * represent significance levels at 0.01, 0.05, and 0.10, respectively (two-tailed test).

Table 6: Two-stage least square estimations

IV stages	Waste/TA (1)	Cost of debt (2)
Waste/TA$_t$		0.0207*
		(0.0119)
ΔWaste facilities$_t$	0.2972***	
	(0.0700)	
Size$_{t-1}$	-0.8937***	-0.0280**
	(0.1403)	(0.0138)
Age$_{t-1}$	-0.3199	-0.1552***
	(0.2086)	(0.0145)
Subsidiaries$_{t-1}$	-0.9780**	0.1990***
	(0.3977)	(0.0300)
TL/TA$_{t-1}$	1.6932***	1.2729***
	(0.5992)	(0.0536)
EBITDA/TL$_{t-1}$	-2.1938***	0.0228
	(0.4232)	(0.0457)
NI/TA$_{t-1}$	2.4428**	-0.5602***
	(1.0921)	(0.1059)
NWC/TA$_{t-1}$	-2.8683***	1.1927***
	(0.5202)	(0.0526)
CL/CA$_{t-1}$	-0.1374*	0.0924***
	(0.0826)	(0.0095)
NITWO$_{t-1}$	-0.2466	0.2985***
	(0.2675)	(0.0221)
OENEG$_{t-1}$	0.5441	-0.3647***
	(0.5476)	(0.0479)
CHIN$_{t-1}$	-0.0246	0.0189*
	(0.1146)	(0.0097)
Fixed effects		
Year-Industry	Yes	Yes
Year-Municipality	Yes	Yes
Observations	129,375	129,375
Adj. R^2	0.13	0.11
Within Adj. R^2	0.006	0.02
Wu-Hausman F-stat	6.17 (p=0.013)	
F-test (of waste/TA)	82.2 ($p<0.0001$)	
Sargan (over-identifying) test	$\chi^2 < 0.0001$ ($p \sim 1$)	

This table reveals a two-stage least square estimation of equation 1 with the change in the number of available waste facilities within 50 kilometers as an instrumental variable of firms' total waste intensity. Section 4.2.1 describes the instrument, all other variables are defined in table A.1 of Appendix A, cost of debt follows the construct of Minnis (2011), and all other continuous variables are winsorized at the 1% and 99% levels. ***, **, and * represent significance levels at 0.01, 0.05, and 0.10, respectively (two-tailed test).

Table 7: Lenders' pricing of SMEs' pollution when providing new debt

Dep = Cost of debt_t	New debt (1)	Alt. new debt (2)	New equity (3)
$\text{Waste/TA}_t \times \text{New debt}_{t-1}$	0.0017^{**}	0.0008^{*}	
	(0.0007)	(0.0005)	
$\text{Waste/TA}_t \times \text{New equity}_{t-1}$			-0.0003
			(0.0013)
Waste/TA_t	0.0010^{***}	0.0010^{***}	0.0012^{***}
	(0.0004)	(0.0004)	(0.0004)
New debt_{t-1}	0.4663^{***}	0.5330^{***}	
	(0.0231)	(0.0159)	
New equity_{t-1}			0.0872^{***}
			(0.0312)
$\textit{Controls}_{t-1}$	Yes	Yes	Yes
Fixed effects			
Year-Industry	Yes	Yes	Yes
Year-Municipality	Yes	Yes	Yes
Observations	129,375	129,375	129,375
Adj. R^2	0.18	0.18	0.17
Within Adj. R^2	0.09	0.10	0.08

This table provides estimation results for equation 1 including an interaction term between waste intensity and new debt or equity at time $t-1$. The definition of new debt and equity follows Naranjo et al. (2022). Column 1 applies the main definition of net interest-bearing debt (NIBD) to measure new debt. Column 2 uses the restricted definition of NIBD with fewer liability items included. Column 3 includes new equity. All estimations include year-industry fixed at the two-digit NACE industry code and year-municipality fixed effects. Standard errors are clustered at the firm level and shown in parentheses. All variables are defined in table A.1 of Appendix A, cost of debt follows the construct of Minnis (2011), and all other continuous variables are winsorized at the 1% and 99% levels. ***, **, and * represent significance levels at 0.01, 0.05, and 0.10, respectively (two-tailed test).