Investigating the Effects of Firm-Level Waste Management on Bank Lending Decisions: Evidence from the US Syndicated Loan Market

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Abstract

Global waste generation presents significant implications for climate change, public health, and environmental pollution, yet it remains underexplored in corporate sustainability research. This study investigates the relationship between firms' waste management practices and their bank loan spreads by analysing a sample of 1,636 syndicated loans to U.S. public companies from 2010 to 2023. Our results show that firms with poor waste management practices incur higher loan spreads and fees, particularly those with higher risk, weaker corporate governance, and less favourable ESG traits. However, waste management practices do not affect nonprice loan terms. These findings enhance our understanding of ESG's role in financial markets by highlighting the ability of banks to address waste externalities, offering important insights for policymakers and practitioners.

Keywords: Waste Management; Bank Lending; Syndicated Loan; Firm Risk; ESG; Corporate Governance

1. Introduction

"Between 400,000 and 1 million people die each year in developing countries because of diseases related to mismanaged waste" (Williams et al., 2019).

Global waste generation is an escalating problem that demands urgent action. If mismanaged, solid waste leads to significant social, economic, and environmental implications, including reduced economic activity, disease transmission, increased pollution, and an inextricable link to climate change (Kaza et al., 2018). Therefore, effective waste management is not only a matter of environmental stewardship but also a cornerstone of public health preservation, the efficient use of resources, and sustainable economic development. Annually, the world generates 2.1 billion tonnes of waste, a figure that is forecast to reach 3.8 billion tonnes by 2050, driven by increasing consumption, urbanisation, and industrialisation (United Nations Environment Programme, 2024). This implies a growth rate twice that of the global population (Kaza et al., 2018). Facing this accelerating challenge, it is crucial that economies are prepared to address growing waste concerns. This is particularly important for the private and public sectors, who have the responsibility and capacity to drive sustainable waste practices.

At the firm-level, superior waste management practices reflect a commitment to the environment and provide tangible benefits such as stronger stakeholder relations, improved operational efficiency, and enhanced financial performance (Gull et al., 2022; Shahab et al., 2022). However, minimising waste remains a challenge for many industries. For example, waste generation issues are often attributed to industrial firms due to the byproducts of production and consumer retail firms, given the complex packaging of goods in high-income economies. Yet, another key player – the financial sector – is often overlooked, despite its significant role in funding the global waste problem.

Banks, as key players in the financing landscape, indirectly contribute to the global waste problem by allocating credit to firms who need to sufficiently consider their environmental impact or waste generation. While their primary focus has traditionally been on assessing borrowers' financial default risk, the landscape of factors influencing banks' lending decisions has shifted significantly. Increasing attention on climate change and decarbonisation has driven policymakers to question how environmental and climate-related risks are being addressed by the financial sector. Although banks cannot lower physical emissions or waste like industrial firms, they can influence positive business ethics by charging lower loan spread or allocating credit to firms with sustainable and socially responsible practices or vice versa. Furthermore, they can also ensure ongoing adherence to these practices through their information advantages and ability to monitor borrowers (Diamond, 1984).

Considering this, policymakers and regulators have started encouraging banks to incorporate environmental and social considerations into their lending frameworks (EBA, 2020; ECB, 2020). As a result, many banks have enlisted as signatories of initiatives like the United Nations Environment Programme Finance Initiative (UNEP FI) and the Equator Principles, improving their ability to integrate corporate social responsibility (CSR) and environmental, social and governance (ESG) factors into their lending decisions (Becchetti & Manfredonia, 2022; Goss & Roberts, 2011; He et al., 2021; Scholtens, 2009).

Empirically, prior studies support this notion, finding that bank loan prices reflect firms' environmental performance. This includes indirect measures of environmental performance such as firms' ESG or CSR ratings (Cai & He, 2022; Drago & Carnevale, 2020; Nandy & Lodh, 2012), and direct measures such as borrowers' physical pollutant quantities. For example, studies have found positive associations between loan prices and firms' carbon emissions, greenhouse gas (GHG) emissions, fossil fuel reserves, and toxic chemical emissions (Chen et al., 2021; Delis et al., 2024; Ho & Wong, 2023; Kleimeier & Viehs, 2021). However, the waste management perspective has been entirely overlooked, and it remains uncertain whether firms' waste generation is considered in cost of capital decisions. Therefore, given the urgency of addressing the escalating global waste problem, the purpose of this study is to fill this gap by investigating the research question: *whether and to what extent do banks incorporate firms' waste management practices into their loan pricing decisions?*

Using a sample of U.S. listed firms from 2010 to 2023, we conduct an ordinary least squares (OLS) regression and find a significantly positive relationship between firms' waste generation and bank loan spreads. This suggests that banks incorporate firms' waste intensities into their loan pricing decisions and penalise less sustainable firms with higher financing costs or vice versa. This finding is robust to different combinations of fixed effects, alternative measures of waste and loan pricing. We then exploit the cross-sectional heterogeneity of the sample to provide evidence on the channels driving the effect of firms' waste management practices on bank loan spreads. Through subsample analyses, we find evidence to suggest that firms exposed to higher risk, weaker corporate governance, and less preferable ESG characteristics, and those headquartered in Republican states are subject to higher loan prices per unit of waste intensity.

Our findings make two important contributions to the literature. Firstly, we advance the understanding of how corporate environmental performance influences firms' costs of capital. Specifically, we shed light on the effect of firms' waste management practices (a direct measure of corporate environmental performance) on the pricing of their bank loan contracts. The extant literature largely focuses on the effects of corporate environmental performance on capital markets, particularly the equity and bond markets (e.g., Attig et al., 2013; Bolton & Kacperczyk, 2021; El Ghoul et al., 2018; Schneider, 2011). However, since bank loans are the largest source of external financing, and structurally and economically differ to traditional capital market instruments, it is crucial to understand the factors that influence their terms (Drago & Carnevale, 2020). Thus, our findings offer valuable insights for policymakers by highlighting the significant role that financial institutions play in funding ethical business practices, therefore underscoring the importance of their oversight. Additionally, the results are insightful for bank managers to understand how borrowers' environmental performance translates to credit risk.

Secondly, our study extends the literature exploring the financial implications of firms' waste management practices. By building upon the existing literature that connects waste management to firms' financial outcomes including cash holdings, and firm performance (e.g., Benjamin et al., 2020; Gull et al., 2022; López-Cabarcos et al., 2024; Pham et al., 2024), this study provides novel evidence of the effects of waste management on firms' costs of capital via their loan financing costs. This insight is relevant for firm managers to better understand the factors influencing their loan prices, allowing them to minimise their costs of capital by improving their waste management practices, and thus enhance firm value.

The remainder of this paper is structured as follows. In Section 2, we present an overview of the extant literature, and based upon the identified gaps, devise the study's hypotheses. Section 3 presents data collection and sample. Sections 4 and 5 present the empirical analysis, including the methodology, results, and discussions. Finally, Section 6, presents the concluding remarks.

2. Literature Review and Hypotheses Development

2.1 The Role of Banks and How ESG is Incorporated into Lending Frameworks

Banks play a crucial role in the financial system by acting as intermediaries between depositors and borrowers. This intermediation promotes economic development, supports the commercialisation of innovation, and enhances financial stability (King & Levine, 1993; Levine, 2005). Unlike capital markets, which rely on public information to screen investments, banks can uniquely access firms' private information when lending (Agarwal & Hauswald, 2010). This ex-ante knowledge advantage reduces the information asymmetry between banks and borrowers, mitigating adverse selection (Diamond, 1984). Moreover, it enables banks to translate the needs and desires of depositors into suitable lending decisions (Scholtens, 2006), which can then be continuously monitored to mitigate other principal-agent problems that may arise from moral hazards (Diamond, 1984; Herbohn et al., 2019). Collectively, these information advantages minimise the likelihood of banks' financial losses from bad debts, which are inevitably incurred by depositors and shareholders.

Ultimately, this ability to screen and monitor borrowers is crucial for banks to optimise the profitability and risk of their loan portfolios, enabling them to maximise shareholder profits. Particularly, banks' information advantages are crucial for enhancing the effectiveness of their loan risk management systems. While many of their on-balance sheet risks can be transferred to third parties (e.g., through financial derivatives), banks are exposed to numerous other risks that are non-diversifiable (Santomero, 1997). For example, borrowers' credit risk, which reflects the possibility of default or failure to meet contractual obligations, is non-diversifiable and must be absorbed by banks after they have entered loan contracts (Santomero, 1997). Therefore, to minimise their exposure to this risk, it is crucial for banks to leverage their ex-ante information advantages during loan screening processes to ensure that credit risk is effectively considered. This is typically achieved by assessing a borrower's likelihood of default, and their loss given default (Attig et al., 2024). Intuitively, and in line with traditional theory, banks will demand higher returns through higher loan spreads to compensate for lending to firms with greater default risk.

However, over the past few decades, the financial risk landscape has changed significantly. Alongside financial returns, a paradigm shift has occurred, with investors increasingly prioritising CSR and ESG performance in their portfolios. For example, as of 2023, over 14,500 funds across Europe, Asia and the Americas included references to ESG in their prospectuses.[1] In response to this growing focus, many firms now report and disclose their ESG performance to signal their commitment to sustainability and avoid being overlooked by ESG-conscious investors. Otherwise, they may be exposed to ESG risks which can negatively impact their reputation, financial performance, and overall viability (Giese et al., 2019).

Given the likelihood of these ESG risks materialising into decreased future cash flows, many banks have started integrating environmental and social considerations into their lending decisions (Becchetti & Manfredonia, 2022; Goss & Roberts, 2011; He et al., 2021; Hrazdil et al., 2024; Scholtens, 2009). Many have also committed to initiatives like the Equator Principles and the UNEP FI, which promote sustainable practices in project finance (Degryse et al., 2023; Scholtens & Dam, 2007).[2] Additionally, banking authorities are increasingly mandating the inclusion of ESG factors into lending decisions. For example, the European Central Bank has advised that by the end of 2024, all European banks must integrate climate-related and environmental risks into their loan pricing decisions, in line with the guidelines of the European Banking Authority (EBA, 2020; ECB, 2020). Consequently, banks are expected to increasingly account for environmental and climate-related risks in their lending decisions moving forward.

2.2 Corporate Environmental Performance and Bank Loan Pricing

Given these growing concerns about environmental risks, particularly at the firm-level, there has been an increase in empirical literature exploring its effects on costs of capital. Typically, most studies have explored the impact of corporate environmental performance on equity and bond markets (e.g., Attig et al., 2013; Bolton & Kacperczyk, 2021; Chava, 2014; El Ghoul et al., 2018; Schneider, 2011). Empirically, the findings of these studies are that firms with greater environmental performance are associated with lower costs of capital.

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[1] https://www.bloomberg.com/professional/insights/data/esg-funds-what-makes-for-good-performance/
[2] The Equator Principles were established in 2003 to provide a framework for financial institutions to identify and control social and environmental risks. Currently, 128 global banks are signatories. Similarly, the UNEP FI was founded in 1992 to foster sustainable development from financial institutions. It currently has 345 signatories.

In the syndicated loan market, research exploring the link between environmental performance and the cost of bank loans is relatively more scarce. From a theoretical perspective, the cost of bank loans should be lower for firms with greater environmental performance. The most common line of reasoning used to support this association is the stakeholders' orientation theory, which proposes that banks incorporate firms' environmental performance into their lending decisions to ensure their long-term objectives align with the collective interests of their stakeholders (Freeman, 1984). Given that banks' financing decisions can indirectly impact the environment, and thus affect all stakeholders, banks must meet stakeholder expectations by making sustainable lending decisions. Cheung et al. (2018) support this theory, finding evidence that firms in more stakeholder-oriented countries with greater CSR performance benefit from lower loan costs. Thus, by incorporating firms' environmental performance into their lending decisions, banks can maintain strong stakeholder relationships and avoid unnecessary costs, ultimately gaining a competitive advantage (Jones, 1995).

The second line of reasoning supporting the notion that banks incorporate firms' environmental performance into their loan pricing decisions is the legitimacy theory. The legitimacy theory proposes that firms align their operations with the laws and norms of society, thereby presenting themselves as 'legitimate' to stakeholders (Dowling & Pfeffer, 1975). Accordingly, to comply with the regulations and expectations of society, banks should promote sustainable investments by financing environmentally friendly projects (Berrone et al., 2017). From the borrowers' perspective, firms will exhibit legitimacy to signal to lenders their lower environmental risk and increased stability of future cash flows, thus reducing their credit risk and allowing them to obtain cheaper external financing (Attig et al., 2024).

This notion that banks integrate firms' environmental performance into their loan pricing decisions is also supported empirically. Specifically, prior studies have explored two measures of corporate environmental performance. First, some studies use indirect measures of environmental performance through ratings. For example, Cai and He (2022) find that banks offer lower loan spreads to firms with higher environmental ratings, consistent with the findings of Nandy and Lodh (2012). Similarly, Drago and Carnevale (2020) find a positive relationship between European firms' CSR ratings and their loan spreads. More recently, Attig et al. (2024) also highlight that banks charge higher loan spreads to firms that disclose negative environmental impacts. However, these findings are not unanimous at the firm-level. For example, Hoepner et al. (2016) find no relationship between sustainability ratings and loan costs at the firm-level, although they do find a relationship at the country-level. Ultimately, using ratings as an indirect approach presents several limitations, including subjectivity in what is being measured and potential errors in how it is measured (e.g., see Berg et al., 2019; Christensen et al., 2021; Gibson et al., 2019). These limitations may cause biased measures through rating divergences (Kleimeier & Viehs, 2021).

To counteract the limitations of ratings, another branch of studies takes a direct approach to measuring environmental performance through the examination of physical pollutant quantities. Firstly, Delis et al. (2024) find that following the 2015 Paris Agreement, banks price climate-risks of firms with higher fossil fuel reserves through higher loan spreads. Several studies then explore the association between carbon emissions and bank loan prices. For instance, Kleimeier and Viehs (2021) find that in a sample of international syndicated loans, banks charge higher spreads to firms with higher carbon intensities. Ehlers et al. (2022) find similar results, but only following the Paris Agreement. Finally, Zhu and Zhao (2022) also examine the impact of carbon intensity on loan spreads in China, with findings consistent to those aforementioned.

Beyond carbon emissions, Ho and Wong (2023) investigate the effect of GHG emission intensity on bank loans, finding that since the Paris Agreement, banks in emerging markets price climate-related risks into their loan spreads. Furthermore, Chen et al. (2021) find a positive and significant relationship between toxic chemical emissions and loan spreads. Thus, banks generally charge higher loan spreads to firms with higher pollution levels. This is especially important because, in many cases, this information is not publicly available, making banks more efficient than capital markets at pricing in these pollution externalities. However, while the existing empirical evidence supports this trend for high-profile measures like carbon and GHG emissions, there is no study yet that investigates whether banks consider firms' waste generation in their lending decisions.

2.3 The Link Between Waste Management Practices and Bank Loan Pricing

Investigating the link between firms' waste management practices and loan costs is essential to understand how the private sector prices the global waste issue, helping to prevent it from escalating further. Currently, mismanaged waste presents significant environmental, social, and economic implications for numerous stakeholders. In particular, solid waste generation and low toxic waste recycling account for approximately 5% of global GHG emissions, primarily driven by methane emissions from landfills and open dumps (Kaza et al., 2018). Additionally, mismanaged waste pollutes waterways and soil, hinders economic development by reducing tourism in developing countries, and, when burned, releases toxic chemicals linked to respiratory and neurological diseases (Kaza et al., 2018; Williams et al., 2019). Despite these negative attributes, solid waste remains forecast to increase at twice the rate of the global population (Kaza et al., 2018). Against this backdrop, it is pertinent to examine the extent to which banks incorporate waste management considerations into their loan pricing strategies, and whether capital allocation adequately rewards firms with superior waste management practices.

Previous studies have found that firms' waste management practices can have tangible impacts on their financial characteristics. For example, Gull et al. (2022) show that greater waste generation (recycling) is associated with lower (higher) firm performance. Moreover, Benjamin et al. (2020) report that firms with voluntary waste disclosure tend to have greater cash holdings. Similarly, López-Cabarcos et al. (2024) show that water and waste management practices can be value-additive for food companies. In contrast, Pham et al. (2024) find that dirty energy consumption can positively impact firm performance. However, to the best of our knowledge, no study has directly explored the effect of firms' waste management practices on their cost of capital through bank loan spreads. Therefore, considering the factors discussed so far, and the importance of addressing waste issues, this study fills a gap in the literature by investigating the research question: whether and to what extent do banks integrate firms' waste management practices into their loan pricing decisions?

To formulate a hypothesis for this research question, we summarise and connect the aforementioned theories. In accordance with the stakeholders' orientation theory, banks should incorporate firms' waste management practices into their lending decisions to align with stakeholder interests (Freeman, 1984). Second, the legitimacy theory suggests that banks should also align their operations with societal expectations by investing in firms with superior waste management practices (Dowling & Pfeffer, 1975). Finally, firms with poorer waste management practices are exposed to greater future risks of cleanup costs, litigation fees, and fines for non-compliance with environmental regulations (Chen et al., 2021; Schneider, 2011).[3] These future environmental liabilities impose unnecessary opportunity costs on firms, increasing their likelihood of facing cash shortfalls. In turn, this increases their overall risk of default. Therefore, banks should translate these potential liabilities into greater credit risk, thus charging higher loan premiums. Considering these factors, we propose the first hypothesis:

[3] Compliance and litigation costs are an increasingly common risk for firms, particularly those operating in environmentally-sensitive industries. For example, in 2012 BP were charged USD $4.5bn in relation to the Deepwater Horizon oil spill. More recently, Volkswagen were subject to significant legal and financial repercussions (costing over ~USD $33.0bn) due to a violation of emission regulations.

Hypothesis 1: *Banks charge higher loan spreads to firms with poorer waste management practices.*

2.4 The Channels Driving the Effect of Waste Management on Loan Pricing Decisions

Having established the first hypothesis, we now use this subsection to explore the channels driving the effect of waste management practices on lending decisions. Specifically, we examine three potential channels: a risk, governance, and preference channel. Investigating these channels will allow for a more nuanced understanding of the underlying factors driving the association between firm waste and loan prices.

2.4.1 The Nexus Between Firm Risk, Waste Management, and Loan Pricing

As aforementioned, the primary criterion for lending decisions is a firm's credit risk. To mitigate this risk, banks conduct pre-loan screening and ongoing monitoring of borrowers to identify factors that may influence credit risk. For example, studies have shown that firms with greater cash flow volatility are linked to higher idiosyncratic risk (Irvine & Pontiff, 2008). Furthermore, this volatility also increases the probability of cash flow shortfalls, which exacerbates firms' risk of default (Minton & Schrand, 1999). Considering this, banks perceive borrowers with higher risk as more uncertain investments, and thus require higher rates of return (Campbell & Taksler, 2003).

Moreover, and as previously stated, a firm's default risk is exacerbated when it has poor waste management practices due to greater idiosyncratic risks arising from potential future litigation, compliance and cleanup costs (Schneider, 2011; Sharfman & Fernando, 2008). In addition to idiosyncratic risk, Chava (2014) and Sharfman and Fernando (2008) suggest that firms less exposed to environmental risks also tend to have lower systematic risk, thereby receiving lower capital costs. Therefore, firms with poor waste management practices should be perceived by banks to have greater idiosyncratic and systematic risks, increasing their default risk.

Given these factors, banks are likely to impose higher loan spreads on firms with poor waste management practices, particularly if they are already exposed to high-risk factors. Considering this, we form Part A of the second hypothesis:

Hypothesis 2a: *The positive effect of firms' poorer waste management practices on bank loan spreads is more pronounced for firms with higher risk.*

2.4.2 The Nexus Between Governance, Waste Management, and Loan Pricing

Since credit risk is a key factor in lending decisions, banks must have the ability to accurately assess this risk to optimise the profitability of their loan portfolios. Therefore, it is crucial that borrowers provide credible information to help banks effectively quantify credit risk (Bhojraj & Sengupta, 2003). The credibility of this information can be enhanced through strong corporate governance mechanisms, which incentivise firms to improve transparency in their operations and internal controls, as well as disclose their environmental performance. This ultimately enables banks to perform more accurate credit risk assessments, leading to more effective pricing of borrowers' true default risk.

Corporate governance refers to the systems by which companies are operated and controlled, aiming to align management and stakeholder interests while enhancing transparency (Shleifer & Vishny, 1997). Effective corporate governance reduces information risk, which can arise from information asymmetry between banks and potential borrowers (Bhojraj & Sengupta, 2003). Consequently, without strong corporate governance, ex-ante information risk can lead to adverse selection, where banks provide credit to firms with unbeknownst higher credit risk. This leads to an inefficient allocation of capital.

Similarly, corporate governance plays a critical role in reducing agency risk, which arises when there is a misalignment of interests between managers and stakeholders (i.e., a separation of ownership and control). For example, managers may pursue their own self-interests at the expense of shareholders by neglecting their duties and engaging in risk-shifting and empire-building activities (Bhojraj & Sengupta, 2003; Jensen & Meckling, 1976; Jensen, 1986). In the context of lending, misalignment between managers and lenders can create moral hazards if managers inefficiently use loan proceeds to serve their own self-interests (Chen et al., 2021). Strong corporate governance mechanisms can alleviate this concern by better aligning principal-agent incentives through increased monitoring of management.

Furthermore, stronger corporate governance can improve the predictability of a firm's cash flows by reducing its exposure to future environmental litigation (Kassinis & Vafeas, 2002). This ensures that banks can more accurately assess firms' default risk from future environmental liabilities.

Considering these factors, firms with weaker corporate governance tend to provide less transparent information on their operations and waste management practices, hence creating information asymmetry and potential agency costs that hinder banks from accurately assessing default risk (Chen et al., 2021). As a result, banks are likely to impose higher loan pricing terms to compensate for this additional risk. This leads to Part B of the second hypothesis:

Hypothesis 2b: *The positive effect of firms' poorer waste management practices on bank loan spreads is more pronounced for firms with weaker governance.*

2.4.3 The Nexus Between Firm ESG Traits, Waste Management, and Loan Pricing

Finally, we investigate whether a preference channel influences bank lending decisions, specifically whether banks favour firms with stronger ESG characteristics. To explore this, we test two proxies of borrowers' ESG traits. First, we assess their ESG scores. According to the legitimacy theory, firms with greater ESG performance are perceived as more socially responsible and thus legitimate, making them more attractive to external financing (Attig et al., 2024; Berrone et al., 2017).

Second, we explore borrowers' political leanings, proxied by whether they are headquartered in a Democratic or Republican state. Empirical evidence suggests that Democrats are less likely to invest in demerit goods and tend to demonstrate superior ESG and CSR performance (Di Giuli & Kostovetsky, 2014; Hong & Kostovetsky, 2012). Consequently, borrowers that are headquartered in Republican states are likely to have weaker adherence to ESG standards and, therefore, may face higher loan spreads as their waste generation increases.

Thus, borrowers with higher ESG scores and those headquartered in Democratic states are likely to be preferred by banks, as lending to them signals to stakeholders that the bank is enhancing its legitimacy and social responsibility. Based on this reasoning, we propose the following hypothesis:

> **Hypothesis 2c:** *The positive effect of firms' poorer waste management practices on bank loan spreads is more pronounced for firms with less preferable ESG characteristics, and headquartered in Republican state.*

3. Research Method

3.1 Data and Sample

Our initial sample of syndicated loans to U.S. public companies between 2010 and 2023. This sample was then merged with corresponding firm-level environmental and financial data, as well as annual macroeconomic indicators, to create a combined dataset. Since financial institutions generate minimal direct waste, including loans to this sector would be largely irrelevant to the analysis, as the bank-to-bank lending framework differs significantly from that of other industries. Therefore, and in line with previous studies, firms classified under the GICS financial sector were excluded from the sample. Thus, the combined dataset resulted in 1,636 loan observations from 2010 to 2023. An overview of the sample selection process is available in Appendix Table A1.

3.2 Measuring Waste Management

The key independent variable of our study is a firm's waste management practices, which we proxy using two waste intensity ratios. Specifically, we use *Waste/Sales* and *Waste/Assets*, defined as the proportion of a firm's total solid waste relative to its net sales and total assets, respectively. To construct these variables, we obtain firms' annual solid waste disposed to landfill (in tonnes) from Refinitiv ESG.[4] Additionally, we source the quantity of waste recycled (in tonnes) from the same database, which we use to calculate firms' recycling rates as another proxy for waste management practices (i.e., *Rec_Ratio*, the ratio of recycled waste to total waste). The reason for focusing on waste intensity metrics, rather than absolute measures of firm waste, is to provide a greater comparison between firms of varying sizes and operational scales. However, for robustness, we also analyse absolute measures of total waste (*Waste*), including its subcomponents (i.e., hazardous (*H_Waste*) and non-hazardous (*NH_Waste*)), which are also sourced from Refinitiv ESG.

Using the preliminary waste management data from Refinitiv ESG, Figure 1 portrays an evident upward trend in total firm-level waste generation in the U.S. from 2010 to 2022.[5] Specifically, total firm waste has increased approximately fourfold over the sample time frame,

[4] Refinitiv ESG is a reputable provider of firm-level ESG metrics for over 15,000 firms across 76 countries, equating to a coverage of approximately 88% of the global market capitalisation.

[5] Refinitiv ESG data is charted from 2010 to 2022, with 2023 excluded as annual data is not yet fully available. In all charts, firm-level waste is winsorised at the 1st and 99th percentiles before being aggregated (either by year or sector, depending on the scenario).

highlighting the escalating waste problem and the significant role that firms play in its acceleration.

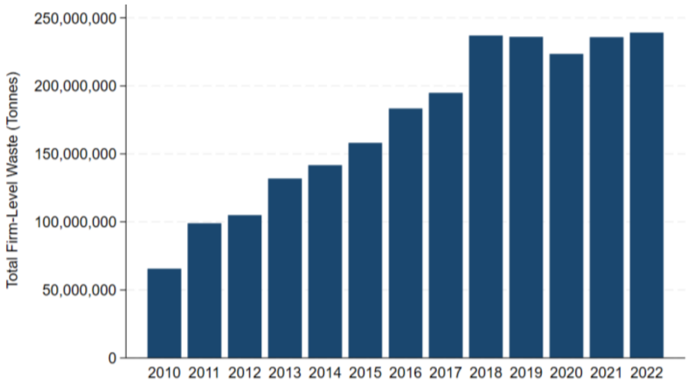

Figure 1: Growth of Aggregate Firm-Level Solid Waste in the U.S.

Furthermore, Figure 2 illustrates that the growth in firm-level waste varies significantly across sectors, with the materials sector being the primary driver. Interestingly, though expected, the financial sector has the lowest waste generation from 2017 onwards. As aforementioned, this is intuitive given that financial institutions are service-based rather than production-based, and therefore have little physical waste. This reinforces the importance of our research question, ensuring that, despite having low waste generation themselves, financial institutions play their part in reducing global waste through their lending decisions.

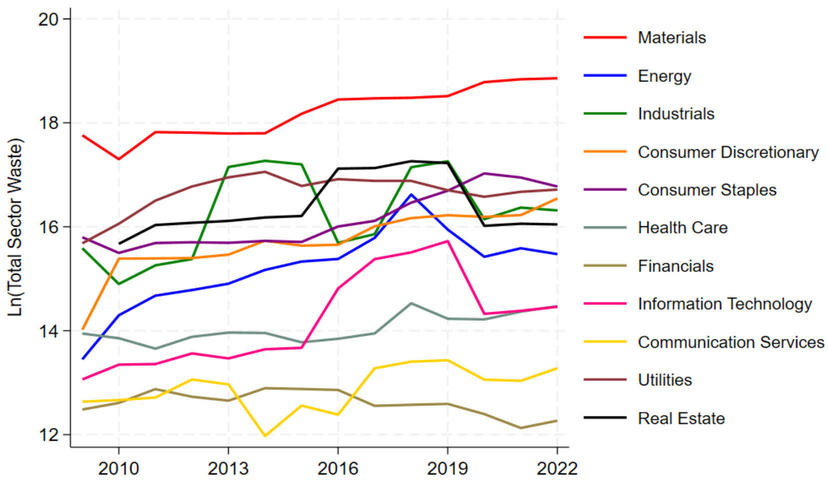

Figure 2: Solid Waste Distribution by GICS Sector

Finally, Figure 3 illustrates how the distribution of firm-level waste varies significantly across U.S. states. Moreover, the comparison between 2010 and 2022 highlights a substantial growth in total firm-level waste, which is dispersed amongst all states. Notably, there has been a relatively uniform increase in waste generation across most states, with pronounced concentrations in the East North Central region and along the coastal perimeter. Specifically, Washington, Colorado and Virginia remain high-level contributors of waste in both 2010 and 2022. Thus, this broad increase in firm waste across the U.S. highlights the significance of this nationwide issue, and how it extends beyond the responsibility of any one given state.

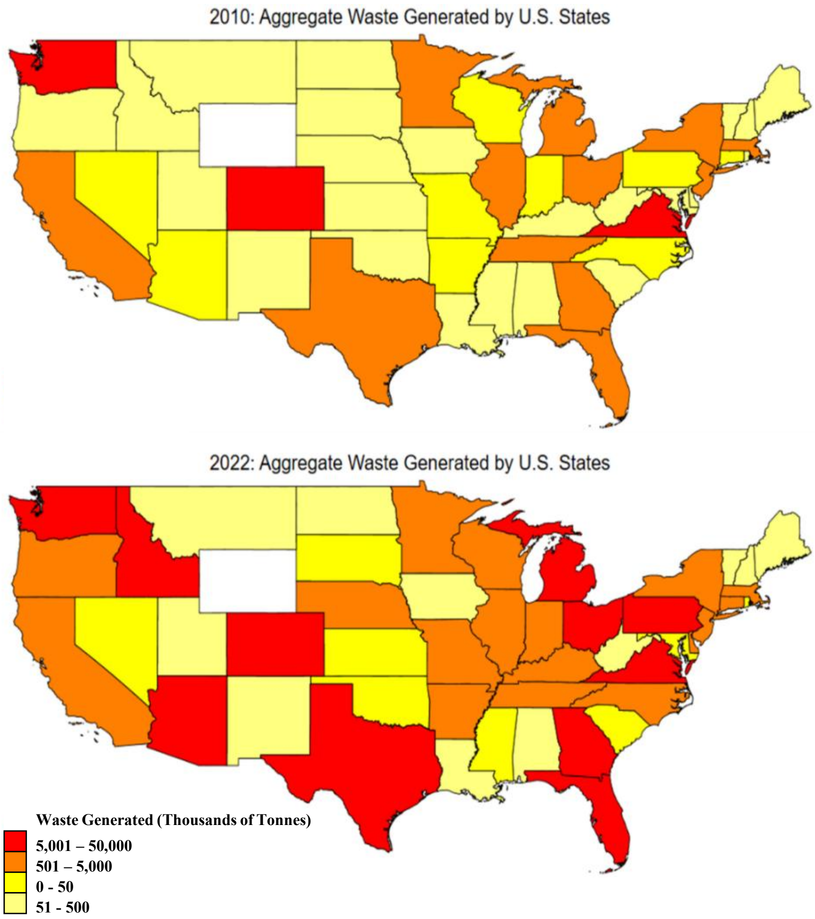

Figure 3: Aggregate Firm-Level Waste Generated by U.S. States in 2010 and 2022

3.3 Measuring Bank Loan Pricing

The dependent variable of our study is the price of bank loans, proxied by the all-in spread drawn rate (AISD). The AISD represents the amount a borrower pays in terms of basis points over the London Inter-Bank Offered Rate (LIBOR) or LIBOR equivalent for each dollar drawn down. It also includes any annual (or facility) fee paid to the lending group. We obtain all loan-level data from LPC DealScan, a comprehensive database that covers a range of terms and conditions of global loan transactions. Despite its renowned reputation, a disadvantage of using DealScan alongside Refinitiv ESG is that they do not provide the same identification variables. As such, we utilise Compustat NA as an intermediary database to merge DealScan tickers with CUSIPs, before merging the DealScan data with the Refinitiv ESG CUSIPs. This introduces a minor limitation to the external validity of our sample due to the loss of some observations during the merging process. However, this trade-off ensures the use of appropriate and reliable data from DealScan and Refinitiv, thereby enhancing our statistical analysis and construct validity.

3.4 Measuring Control Variables

We also include control variables for borrower- and loan-level characteristics, as well as macroeconomic factors, to mitigate potential biases and strengthen the internal validity of the analysis. Specifically, we use firm-level controls to account for alternative borrower characteristics that may influence bank loan pricing decisions. The inclusion of these controls is crucial to isolate the effect of waste management from other confounding factors that banks may consider in their lending decisions. Consistent with prior research (e.g., Chen et al., 2021), we control for the financial characteristics *Ln(Assets)*, *Leverage*, *MTB*, *Tangibility*, *Profitability*, and *Shareprice_vol*. These variables are sourced from Worldscope and Datastream. Importantly, we lag all firm-level explanatory variables (including Refinitiv ESG waste management data) by one period to ensure that lending decisions are based on past firm characteristics, rather than current information that may not have been available to the bank at the time of loan origination.

Furthermore, we include loan-level controls to account for variations in loan terms that could affect spreads independently of firm waste. Specifically, we control for *Ln(Maturity)*, *Ln(Size)*, *Covenant*, *Performance*, *Collateral,* and *Lead Arrangers*, [6] all of which are sourced from DealScan. Moreover, we also use data from DealScan to control for loan effects, including loan purpose and type, to ensure that loan prices in our analysis are not influenced by variations in the purpose or structures of the loans.

[6] Degryse et al. (2023) explain that in loan syndicates, lead arrangers establish and maintain relationships with borrowers, and as such are the entities responsible for determining the loan price. On the other hand, participating banks (such as providers, participants, joint arrangers, lenders, underwriters, etc.) utilise information provided by lead arrangers in their more-distant relationship with the borrower (Sufi, 2007).

Finally, we source macroeconomic characteristics from Datastream, including *Credit Spread* and *Term Spread*, to ensure that broader macroeconomic conditions that may affect lending decisions do not confound the impact of firm waste. For example, during periods of rising interest rates and reduced economic activity, banks may tighten credit allocations and raise loan prices uniformly, irrespective of firm waste levels. Complete information regarding variable definitions and their sources can be viewed in Table A2 in the Appendix.

3.5 Estimation model

Following Chen et al. (2021), we employ an OLS regression in the baseline analysis to test the effects of firms' waste management practices on bank loan spreads. An OLS regression is highly applicable for our study, as it enables us to effectively capture and interpret the hypothesised positive (negative) relationship between firms' waste intensities (recycling ratios) and loan spreads while controlling for other confounding variables. The specific OLS regression is outlined below:

$$Ln(Spread)_{i,t} = \beta_0 + \beta_1 Waste_{i,t-1} + \theta' X_{i,t-1} + \delta' Z_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \quad (1)$$

Where $Ln(Spread)_{i,t}$ is the dependent variable, denoting the lending spread over LIBOR for loan i issued in year t. The key independent variable of $Waste_{i,t-1}$ denotes the one-year lagged proxy for firm i's waste management practices in year *t-1*, including its $Waste/Sales_{i,t-1}$, $Waste/Assets_{i,t-1}$, and $Rec\_Ratio_{i,t-1}$. Furthermore, $X_{i,t-1}$ and $Z_{i,t}$ represent vectors of firm- and loan-level control variables, respectively, where the firm-level controls are lagged by one-year. γ_i and γ_t represent firm and year fixed effects, and $\epsilon_{i,t}$ represents the error term of the regression. The regression will also control for loan effects, including loan type and loan purpose. As per prior studies, we cluster standard errors at the firm-level in all specifications to account for potential within-firm correlations (e.g., Chen et al., 2021; Kleimeier & Viehs, 2021)

3.6 Descriptive Statistics

Upon finalising the sample selection process, a total of 1,636 loans to 268 firms were recorded from 2010 to 2023. These observations span a diverse range of industries, enhancing the sample's validity and representativeness by providing insights into waste management practices across various sectors. Notably, the chemicals industry had the highest frequency of observations, followed by the hotels, restaurants and leisure industry, and the food products industry. A full breakdown of the distribution by industry can be observed in Table 1.

[Insert Table 1 here]

The descriptive statistics for the sample are presented in Table 2. All continuous variables are winsorised at the 1^{st} and 99^{th} percentiles to mitigate the effects of outliers. The dependent variable *Ln(Spread)* falls within the range of 2.862 and 6.215 (17.50 and 500.20 basis points (bps)), with an average value of 4.855 (128.38 bps). Concerning the independent variables, the mean value of the natural logarithm of *Waste* is 10.932, implying that firms in the sample generate an average annual waste of 55,938.04 tonnes. From this, the mean ratios of the waste intensity variables *Waste/Sales*, *Waste/Assets*, and *Rec_Ratio* are 0.368, 0.172 and 0.575 respectively. For the other explanatory variables, the mean natural logarithms of *H_Waste* and *NH_Waste* are 7.761 and 10.716, respectively.

Regarding the loan terms, the average value of *Ln(Maturity)* is 3.579 (approximately 35.84 months, or just under three years) and the mean value of *Ln(Size)* is 6.984, which equates to approximately USD $1.08 billion. Finally, the average number of lead arrangers in a loan syndicate is 5.382, with some facilities being led by a maximum of 26 arrangers. Overall, these summary statistics are similar to those used in prior studies (e.g., for waste data see Gull et al. (2022); for loan data see Chen et al. (2021)).

[Insert Table 2 here]

4. Empirical Results

4.1 Baseline Results

[Insert Table 3 here]

The regression results of the baseline analysis are presented in Table 3. As hypothesised, the results display a positive relationship between firms' waste intensities and the subsequent spreads of their bank loans. Specifically, the coefficients on *Waste/Sales* and *Waste/Assets* are positive and statistically significant at the 1% level, suggesting that firms with higher waste intensities are subject to higher lending costs. Moreover, this relationship holds across all specifications, including with firm-, macro- and loan-level controls, as well as firm and year fixed effects. Particularly, the models fit best when all control variables and fixed effects are included (i.e., columns (3), (6), and (9)), with R-squared values of 0.791, 0.792 and 0.804 for *Waste/Sales*, *Waste/Assets* and *Rec_Ratio*, respectively.

The results also carry important economic significance. The magnitude of the positive coefficients imply that a one-standard deviation increase in an average firm's *Waste/Sales* ratio will result in a 23.55bp increase in their loan spreads. Given the average maturity and loan size of the sample, this translates into an additional $7.58 million in total interest payments for an average borrower.[7] In terms of firms' *Waste/Assets*, the results are similar in economic significance; a one standard deviation increase translates to a 19.57bp increase in loan spreads, which results in an additional $6.30 million in interest payments across the average loan in the sample. Thus, this demonstrates that the positive association between firms' waste generation

[7] Impact of a one standard deviation increase in *Ln(Spread)* = 0.0758 × 2.222 = 0.168. Since the sample mean *Ln(Spread)* is 4.855, the new *Ln(Spread)* is 4.855 + 0.169 = 5.023. Therefore, the impact of a one standard deviation increase in *Waste/Sales* on the loan spread (in bps) is = $e^{5.023}$ - $e^{4.855}$ = 23.55bps. Since the average loan size is $e^{6.984}$ = $1,079.23m, and the average maturity is $e^{3.578}$ = 35.84 months = 2.99 years, this implies that a one standard deviation increase in *Waste/Sales* will lead to 23.55bps × 1,079.23m × 2.99 = $7.58 million in additional interest.

and their loan spreads is both statistically and economically significant, reaffirming the importance of policymakers and practitioners considering this factor in lending frameworks.

Within Table 3, columns (7)–(9) also present the relationship between a firm's recycling ratio and the cost of its bank loans. As expected, the results suggest an inverse relationship, implying that firms with higher recycling rates are rewarded with lower loan spreads. Specifically, a one standard deviation increase in the average firm's recycling rate translates to a 1.73bp decrease in loan spreads. Although these results are statistically insignificant, they supplement the central hypothesis that banks reward firms with superior waste management practices with lower loan costs. However, to address the statistical insignificance, it may be valuable for policymakers and practitioners to accord greater emphasis on firms' recycling practices in lending frameworks. This would better promote the transition to a circular economy.

Regarding the control variables, the coefficients largely reflect the values obtained in previous studies in both sign and magnitude. Particularly, *Ln(Assets)* consistently displays a negative relationship with *Ln(Spread)*, suggesting that larger firms receive cheaper loan financing. This is intuitive, as larger firms are more capable of absorbing cash flow shocks, and thus have less default risk (Goss & Roberts, 2011). Similarly, *MTB* and *Leverage* display positive associations with loan spreads. This intuitively implies that firms with higher growth opportunities (and/or market mispricing) and higher amounts of debt translate into higher credit risk, and thus receive higher loan spreads. These findings are supported by numerous prior studies both theoretically and empirically (e.g., Chava, 2014; Chen et al., 2021; Goss & Roberts, 2011; Ho & Wong, 2023). Finally, the positive coefficient on *Shareprice_vol*, albeit insignificant, supports the notion that equity volatility is a significant driver in the cross-sectional variation of yields (Campbell & Taksler, 2003).

In contrast to the results in Chen et al. (2021), we find a positive association between loan spreads and their maturities, the use of performance pricing conditions, and the credit and term spreads. However, these findings are statistically insignificant and economically immaterial, suggesting that these variables do not have a strong influence on loan pricing decisions. These findings are consistent with Kleimeier and Viehs (2021).

4.2 Robustness Tests

4.2.1 Different Combinations of Fixed Effects

Having established the baseline results, we now explore their robustness by testing various combinations of fixed effects (FEs). FEs control for unobserved heterogeneity arising from time-invariant characteristics, allowing us to better isolate the effect of firm waste on loan spreads. Thus, exploring different combinations of FEs enables us to sensitise the findings against alternative specifications, ensuring that the observed relationships between waste management practices and loan spreads are not driven by unobservable firm or loan-specific factors.

In the baseline analysis, we controlled for firm and year FEs, as well as loan purpose and type. In this section, we now test different combinations of these FEs, as well as the substitution of firm FEs for industry FEs. Importantly, firm and industry FEs are not used simultaneously to avoid multicollinearity issues.

Ultimately, we test three specifications, all of which include year FEs to ensure that time-varying macroeconomic conditions are controlled throughout. First, we test firm FEs while excluding loan FEs, enabling us to isolate the effect of firm waste on loan spreads without accounting for loan-specific variations. Next, we test industry FEs while excluding loan FEs, allowing us to compare the first test to distinguish whether the effects of waste management practices are driven by firm-specific or industry-wide characteristics. Finally, we test loan FEs while excluding both firm and industry FEs, which allows us to explore whether variations in loan spreads are influenced more by loan-specific factors rather than firm- or industry-specific characteristics.

[Insert Table 4 here]

The results of the analysis using different combinations of FEs are presented in Table 4. Panel A shows that a positive and significant relationship between *Waste/Sales* and *Ln(Spread)* holds in column (1) when using only firm and year FEs, and excluding loan FEs, but becomes insignificant in column (2) when substituting firm FEs with industry FEs. This implies that firm-specific factors play a greater role than industry-specific factors in driving the relationship observed in the baseline analysis. Furthermore, when excluding both firm and industry FEs and only using loan FEs, there remains a significantly positive relationship, suggesting that loan-specific factors also play a role in the relationship between firm waste and loan spreads. However, this coefficient is weaker in magnitude relative to the result in column (1), suggesting that firm-level factors are greater drivers of the relationship between firm waste and loan spreads. These results and interpretations are mirrored in Panel B when investigating the different combinations of FEs on *Waste/Assets*.

In Panel C, we explore the effects of these FEs on the relationship between *Rec_Ratio* and *Ln(Spread)*. Interestingly, the significantly negative result in column (2) highlights that industry-specific factors play a greater role than firm-level factors in driving the relationship between firms' recycling practices and loan spreads. Moreover, this impact is similar in magnitude and sign to the coefficient obtained using the loan-specific factors in column (3). These relationships provide additional evidence to the baseline results and validate the notion that firms with superior waste practices (i.e., lower waste intensities and greater recycling ratios) are rewarded with lower bank loan spreads.

4.2.2 Absolute Measures of Waste Management

Although the waste intensity ratios in the baseline analysis improve the comparability of observations among firms, a key limitation is that they are inherently noisier than absolute measures of waste. This is because ratios introduce the potential for measurement errors not only in the numerator but also in the denominator. Additionally, two firms with similar waste intensities may produce vastly different amounts of total waste, and it is aggregate waste that ultimately imposes costs on the environment and society. Given that regulations are more likely to target firms with higher total waste, it is expected that banks will perceive firms with greater aggregate waste as higher risk, and therefore charge higher loan prices.

Thus, we now test the absolute measures of total waste (*Waste*) and its non-hazardous (*NH_Waste*) and hazardous (*H_Waste*) subcomponents by substituting them as independent variables into Equation (1). For context, hazardous waste is any waste that poses threats to the environment or public health, and is typically either ignitable, oxidising, toxic, corrosive or radioactive. In contrast, non-hazardous waste poses no risk of infections or injury, and includes waste products like plastic, cardboard and clean glass.

[Insert Table 5 here]

The results from the robustness test of absolute waste measures are displayed in Table 5. As anticipated, the results show that the coefficient on *Waste* is significantly positive, implying that higher levels of aggregate firm waste are associated with higher loan spreads. Notably, this relationship is primarily driven by firms' non-hazardous waste, demonstrated by the significantly positive coefficient on *NH_Waste* that is similar in magnitude to the coefficient on *Waste*. This is interesting because, due to the inherently higher risks associated with hazardous waste, one would expect stakeholders and financiers to place greater emphasis on it rather than on non-hazardous waste (Gull et al., 2022).

Overall, the results from this analysis align with the findings in Gull et al. (2022), who show that total firm waste and its subcomponents have tangible impacts on firm performance. However, the insignificant and weak coefficient on *H_Waste* indicates that hazardous waste is not as important as non-hazardous waste for banks in their lending decisions. Thus, this validates the baseline findings and aligns with our first hypothesis that banks incorporate firms' waste into their loan pricing decisions.

4.3 Channels Analysis

Thus far, the baseline analysis suggests that banks offer higher (lower) loan spreads to higher waste-generating (recycling) firms, aligning with the first hypothesis. In this section, we investigate the second hypothesis by exploiting the cross-sectional heterogeneity of the sample to explore the channels through which this relationship is driven. The remainder of this section explores three channels: a risk, governance, and preference channel, which we test using subsample analyses following Benlemlih and Yavaş (2023). Specifically, we halve the sample with respect to the median value of the channel variable of interest, creating samples of (i) high risk versus low risk, (ii) weak governance versus strong governance, and (iii) weak preference versus strong preference. Then, we rerun Equation (1) within each subsample to test the effects of the channels. Importantly, we exclude firm FEs to allow cross-sectional differences to be appropriately examined rather than controlled.

4.3.1 Risk Channel Analysis

In theory, and as per Hypothesis 2a, the relationship between waste practices and loan spreads should be more pronounced for firms facing higher default risks. To test this theory, we examine the effects of three risk variables. Like in Chen et al. (2021), we explore the impacts of a firm's *Z-score*, *Beta*, and *Probability of Default* (*PD*). While Chen et al. (2021) measure expected default frequency using a present market-value measure, we extend the risk analysis by exploring a forward-looking, market-based metric of a firm's probability of default, which also incorporates external macroeconomic factors. We obtain this variable from the National University of Singapore Credit Research Initiative (NUS CRI).

[Insert Table 6 here]

The results of the risk channel subsample analysis are presented in Table 6, with Panel A exploring the effects of *Waste/Sales* and Panel B examining *Waste/Assets*. Overall, the results suggest that the effects of firms' waste management practices on bank loan prices are more pronounced for firms with higher risk. This is demonstrated by the significantly positive coefficients on the low *Z-score* and high *PD* variables in Panels A and B, indicating that banks charge higher loan spreads to waste-generating firms that are more likely to enter bankruptcy within two years (low *Z-score*) or have a higher probability of default over a 12-month horizon (high *PD*). Additionally, there is a positive, significant relationship for firms with above-median *Beta* in Panel A, although this result is not distinct in Panel B.

Overall, these results support the notion that firms with higher risk are of greater concern to debtholders (Campbell & Taksler, 2003; Minton & Schrand, 1999). Specifically, firms with poorer waste management practices likely face higher uncertainty about their ability to meet loan repayments due to potential future environmental liabilities. Thus, this aligns with the second hypothesis that the effects of firms' waste management practices on banks' loan pricing decisions are more pronounced for firms with higher risk.

4.3.2 Governance Channel Analysis

As per Hypothesis 2b, the relationship between waste practices and loan spreads should be more pronounced for firms with weaker corporate governance practices, given the increased opacity and thus higher risk perceived by lenders. To test this theory, we investigate the effects of seven governance variables following Chen et al. (2021). Specifically, we explore the impacts of a range of firm's board characteristics, including *Independent*, *Busy*, *Board Size*, *Duality, Ln(Exec Comp)*, *Attendance*, and *Governance*.[8]

[Insert Table 7 here]

Table 7 presents the results of the governance channel subsample analysis. Panel A explores the role of governance variables on the effect of *Waste/Sales* on *Ln(Spread)*, with generally insignificant findings except in subsamples with higher *Independence* and less *Busy* boards, lower *Ln(Exec Comp)*, and lower *Governance*. This implies that higher waste intensities in these subsamples are associated with higher loan spreads. Similarly, the findings in Panel B closely mirror these results from Panel A; the coefficient of *Waste/Assets* is positively significant in subsamples with higher board *Independence*, lower *Ln(Exec Comp)* and lower overall *Governance*. The latter of these findings – the significantly positive coefficient on waste intensities in firms with low *Governance* – aligns with our second hypothesis that firms with relatively weaker governance face higher loan spreads per unit of waste intensity. This provides evidence to support the theory that strong corporate governance mitigates principal-agent problems and improves informational transparency, which in turn reduces costs of capital (Easley & O'hara, 2004; Shleifer & Vishny, 1997).

However, the results of higher loan spreads for firms with higher board *Independence* and less *Busy* board members are somewhat counterintuitive. Typically, boards with greater independence and less busy directors are indicators of stronger corporate governance due to their ability to more effectively monitor management activities (Chen et al., 2021; Nguyen & Nielsen, 2010). However, our findings provide evidence for the other side of the debate, which

[8] While Chen et al. (2021) measure their attend variable as the proportion of directors who attend below 75% of meetings, we use the average attendance percentage of board members across all meetings, as reported by the firm. Importantly, since the median of *Attend* equals the minimum in our sample, we use the mean value to create the subsamples. Also, while Chen et al. (2021) explore the natural logarithm of a CEO's total compensation, we explore the natural logarithm of the firm-reported total compensation paid to all senior executives. Finally, the *Governance* variable is constructed using a principal component analysis (PCA) of the variables *Independent*, *Busy*, *Board Size*, *Duality*, *Ln(Exec Comp)*, and *Attendance*.

suggests that increased board independence may compromise stakeholder orientation, and lead to inefficiencies arising from inadequate understandings of company-specific affairs (Brochet & Srinivasan, 2014; Shahab et al., 2022). This could explain why firms with higher board independence experience higher loan spreads, despite exhibiting stronger corporate governance. This provides interesting insights for practitioners when reflecting on their governance structures.

In addition, we also extend our governance channel analysis by exploring the effects of a firm's *Board Diversity*. The un-reported results highlight that firms with lower board diversity face higher loan spreads for increases in *Waste/Sales*. This is consistent with our hypothesis that firms with weaker corporate governance (through lower board diversity) are penalised with higher loan spreads for poor waste management practices. This aligns with previous studies that find that female board directors tend to be more ethical in business decision-making, and enhance firms' sustainable performance (Atif et al., 2020; Glass et al., 2016) and decrease their waste generation (Gull et al., 2023).

4.3.3 Preference Channel Analysis

Hypothesis 2c states that the association between waste practices and loan spreads should be more pronounced for firms with less preferable ESG characteristics. To test this, we investigate the effects of two preference variables. First, we explore the political leaning of borrowers, proxied by a dummy variable (*Politic*) that is equal to one if firms are headquartered in a Republican state, and zero if in a Democratic state. Second, we analyse whether banks exhibit a preference for borrowers based on their ESG scores. As hypothesised, we expect that banks favour firms in Democratic states, thus charging higher loan spreads to Republican firms. Additionally, we hypothesise that banks will prefer lending to firms with higher ESG scores, and thus will charge higher loan spreads to firms with low ESG scores.

[Insert Table 8 here]

The results of the preference channel subsample analysis are presented in Table 8. Overall, the results provide evidence to suggest that the effect of firms' waste management practices on bank loan prices is more pronounced for firms with less preferable ESG characteristics. Firstly, this is demonstrated by the positive coefficients in the Republican subsamples, implying that banks charge higher loan spreads to Republican-headquartered firms as opposed to Democratic firms when considering their waste management practices. Although the coefficients are only weakly significant at the 10% level, they hold for both *Waste/Sales* in Panel A and *Waste/Assets* in Panel B. This finding coincides with our hypothesis; since Republicans are less inclined to support ESG initiatives and tend to have inferior CSR performance, debtholders perceive greater environmental risk when lending to Republican-headquartered firms (Di Giuli & Kostovetsky, 2014). As such, the negative effects of waste management practices on firms' loan costs are more discernible for firms headquartered in these states.

Furthermore, we also observe a positive, weakly significant relationship for firms with below median ESG scores in Panel A, although this result is inconsistent in Panel B. This partly indicates that firms with less preferable ESG scores are penalised more than those with high ESG scores with respect to the effects of their waste management practices on their loan costs. Again, this supports our second hypothesis.

4.4 Endogeneity Tests

Thus far, the results suggest that banks incorporate firms' waste management practices into their loan pricing decisions, and to some extent these results are driven by risk, governance and preference channels. However, the internal validity of these results may be vulnerable to endogeneity risk arising from simultaneity, measurement error and omitted variables. For example, the results may suffer from simultaneity if firms initially receive higher loan spreads, and subsequently increase their output and waste to meet the repayments of these higher loan costs. Although we already attempt to mitigate this concern by regressing bank loans on one-year lagged waste management variables, our findings may still be subject to endogeneity. Hence, to address reverse causality, we now employ a two-stage least squares (2SLS) regression.

Secondly, unobservable characteristics may lead to the model failing to account for all relevant variables, leading to omitted variable bias. Particularly, if said omitted variable is correlated with a firm's level of waste, and partly determines a firm's loan price, our regression estimates so far may be biased. To mitigate this risk, we use firm, year and loan fixed effects in models throughout the study, which we also sensitised for robustness. Additionally, to account for potential self-selection bias in observable characteristics, we now also employ a propensity score matching (PSM) test.

Finally, the results thus far may be subject to measurement errors of the key variables. While we already test alternative measures of waste for robustness, we now test alternative proxies of loan pricing using the different fees within the loan contracts (Berg et al., 2016).

4.4.1 Two-Stage Least Squares (2SLS) Estimation

To address simultaneity, we employ a two-stage least squares approach to isolate the effect of firm waste on loan spreads through an instrumental variable. In the first stage, firm waste is regressed on the instrument to generate predicted values that capture the exogenous variation in waste. In the second stage, loan spreads are then regressed on these predicted values to estimate the causal effect of waste intensity on loan spreads.

Ultimately, the effectiveness of this design depends on the instrument used. For an instrument to be valid, it must satisfy two conditions. First, it must meet the relevance condition, meaning it is strongly correlated with the endogenous variable (i.e., firm waste). Second, it must fulfil the exclusion condition, meaning the instrument should affect the dependent variable (i.e., loan spreads) only through the endogenous variable while being uncorrelated with the error term.

Given these conditions, we employ two instruments: industry-year average waste, and a one-year lag in firm waste (in addition to the one-year lag already applied in previous specifications). First, we calculate industry-year average waste using the average annual waste intensity of firms within a particular industry, excluding firm i's waste for that year. This is based on the rationale that a firm's waste is likely correlated to its industry peers due to similarities in business operations, production processes, and regulations. Additionally, since industry-year average waste is unlikely to affect a firm's default risk, it is also unlikely to affect loan spreads (Atif & Ali, 2021). This instrument has been commonly used in other studies (Atif & Ali, 2021; Nadeem et al., 2020; Shahab et al., 2022; Zhu & Zhao, 2022).

Next, we follow Zhu and Zhao (2022) and use a one-year lag in waste intensity as our second instrument. Again, this satisfies the relevance condition, as the continuity of firm operations ensures that successive waste generation is correlated (i.e., waste in period $t\text{-}2$ is correlated with waste in $t\text{-}1$). Moreover, lagged waste may have no correlation with the error term (Zhu & Zhao, 2022). This instrument is also used in numerous other studies (e.g., Benjamin et al., 2020; Gull et al., 2022; Shahab et al., 2022).

[Insert Table 9 here]

Table 9 presents the results from the 2SLS analysis. Panel A displays the effects of *Waste/Sales*, while Panel B explores *Waste/Assets*. Columns (1)-(2) present the first and second stage regressions using industry average waste as an instrument, while columns (3)-(4) report the results using lagged waste as an instrument. Finally, columns (5)-(6) present the results using both instruments simultaneously.

In all first-stage specifications, firms' waste intensities display a significantly positive association with lagged waste and industry average waste (except in column (5) of Panel A), supporting the relevance of these instruments as predictors of firm-level waste. While most F-statistics indicate strong instruments, the relatively low values for the industry average instrument (e.g., 3.86 and 5.47 in Panel A and Panel B, respectively) may suggest concerns about its strength. However, in all specifications, the Cragg-Donald Wald F-statistics significantly exceed the critical values at the 10% level proposed by Stock and Yogo (2005), thereby mitigating concerns about the weakness of our instruments.

In the second-stage regressions, the results highlight the effects of the predicted values of *Waste/Sales* and *Waste/Assets* on loan spreads, controlling for other firm- and loan-level characteristics. Consistent with the baseline analysis and supporting our first hypothesis, all specifications reveal a significantly positive relationship between firms' waste intensities and their loan spreads. This suggests that banks incorporate firms' waste management practices into their loan prices, confirming the robustness of our baseline results to the 2SLS approach and addressing endogeneity concerns.

4.4.2 Propensity Score Matching (PSM)

To account for potential self-selection bias due to observable firm characteristics, we now use a propensity score matching approach (Rosenbaum & Rubin, 1983). We firstly create a dummy variable (*Treatment*) that equals one if a firm's waste intensity is above the sample median, and zero otherwise. We classify firms with *Treatment* equal to one as being in the treatment group, and those with *Treatment* equal to zero as the control group. Next, we match treatment firms to control firms using propensity scores from the predicted estimates of a logit regression of the firm-level control variables in Equation (1). The results of this logit regression are presented in column (1), Panel A of Table 10. Evidently, firms with higher waste intensity are smaller, have higher leverage, more tangibility and less share price volatility.

[Insert Table 10 here]

Using these propensity scores, we then create one-for-one matches between firms with high waste intensity and firms with low waste intensity. We perform matching without replacement, while ensuring that the maximum absolute difference in propensity scores between the treated and matched firms does not exceed 0.1%. As a result, we were able to match 442 observations between the treatment and control groups.

To verify our matching process, we conduct two diagnostic tests to confirm that our observable characteristics are indistinguishable between firms in the treatment and control groups. First, we re-estimate the logit regression in Panel A using the post-match sample, the results of which are presented in column (2). Importantly, the coefficients using the post-match sample are insignificant and smaller in magnitude than the regression using the pre-match sample, indicating that the observable characteristics between the groups are now very similar.

The second diagnostic test explores the mean differences of the observable firm characteristics between the two groups. The results of this test are presented in Panel B of Table 9. Notably, the results suggest that the PSM effectively mitigates the mean differences between firm observables, therefore enhancing the likelihood that variations in loan spreads between the treated and control groups are driven by differences in waste intensity rather than other firm-specific characteristics.

Finally, Panel C presents the propensity score matching estimate of the average treatment effect on the treated, highlighting a significant difference in loan spreads between the treatment and control groups. Specifically, the treatment group displays higher loan spreads across the matched sample, indicating that loan costs are greater for firms with higher waste compared to the otherwise indistinguishable firms that generate lower waste.

4.4.3 Alternative Measures of Dependent Variable: Total Cost of Borrowing and Fees

Finally, we address endogeneity by exploring alternative measures of loan costs to mitigate the possibility of measurement error. In the baseline analysis, loan prices are proxied by the AISD, which reflects the spread of the loan over LIBOR (or LIBOR equivalent) for each dollar drawn down, in addition to any annual (or facility) fee paid to the lender. However, the pricing of loans extends beyond just the spread. Particularly, Berg et al. (2016) highlight that fees are a significant component in the pricing of corporate loan contracts, with approximately 80% of syndicated loans in the U.S. including at least one type of fee.

Thus, we account for fees in the pricing of loans by following the method in Ehlers et al. (2022). Specifically, we construct a variable $Ln(Fees)_{i,t}$, defined as the natural logarithm of the sum of the fees (in bps) incorporated into a loan contract. As per those used in Ehlers et al. (2022) and Berg et al. (2016), these include commitment fees (charged on undrawn loan commitment amounts), upfront fees (charged to lenders upon the closing of a loan contract), cancellation fees (charged against commitment reduction or loan termination), and utilisation fees (charged on the drawn amount of a credit facility). This variable will be substituted for the dependent variable in the baseline analysis, as demonstrated by Equation (2). Finally, the sum of the fees in the contract will also be added to the AISD to create a broader proxy of the total cost of borrowing (TCB), and the natural logarithm of this sum will also be tested as a dependent variable in Equation (2):

$$Y_{i,t} = \beta_0 + \beta_1 Waste_{i,t-1} + \theta' X_{i,t-1} + \delta' Z_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \quad (2)$$

Where $Y_{i,t}$ is either $Ln(Fees)_{i,t}$ or $Ln(TCB)_{i,t}$. As in the baseline analysis, $Waste_{i,t-1}$ represents either $Waste/Sales_{i,t-1}$, $Waste/Assets_{i,t-1}$, or $Rec\_Ratio_{i,t-1}$.

[Insert Table 11 here]

Table 11 presents the results of the analysis using alternative measures of borrowing costs. Overall, the results coincide with the baseline analysis, finding evidence to suggest that banks also incorporate firms' waste intensities into their loan fee pricing decisions. Particularly, all coefficients on *Waste/Sales* and *Waste/Assets* are positive and strongly significant, suggesting that as a firm's waste intensity increases, so too do its loan fees and total cost of borrowing. This aligns with the findings in Chen et al. (2021) and Ehlers et al. (2022), and ultimately supports the proposition by Berg et al. (2016) that fees should be considered when measuring total borrowing costs.

Furthermore, the effect of fees on *Rec_Ratio* in column (6) is negative and statistically significant at the 10% level, indicating that firms with better recycling practices are rewarded with lower fees in their loan contracts. Hence, this supports the findings of Gull et al. (2022) that firms' recycling rates can have tangible impacts on their financial performance. Thus, this supports our first hypothesis that banks favour firms with superior waste management practices in their loan pricing decisions.

5. Additional Evidence

5.1 Effects of Waste Management on Nonprice Loan Terms

Finally, our study also aims to provide additional evidence of the relationship between firms' waste management practices and lending decisions by investigating the effects on nonprice loan contractual features. Previous literature suggests that banks may use nonprice loan features as complementary or alternative methods to mitigate their exposure to risk (He et al., 2021; Ho & Wong, 2023; Javadi & Masum, 2021; Nandy & Lodh, 2012). To validate this claim, multiple nonprice loan terms were substituted as dependent variables in Equation (1).

Specifically, we explore the effects of firm waste on loan size, maturity, and the number of lead arrangers in a syndicate. This is illustrated in Equation (3):

$$Nonprice_{i,t} = \beta_0 + \beta_1 Waste_{i,t-1} + \theta' X_{i,t-1} + \delta' Z_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \quad (3)$$

Where $Nonprice_{i,t}$ represents either $Ln(Maturity)_{i,t}$, $Ln(Size)_{i,t}$, or $Lead\_Arrangers_{i,t}$. As in the baseline analysis, $Waste_{i,t-1}$ refers to several measures of waste management, including $Waste/Sales_{i,t-1}$, $Waste/Assets_{i,t-1}$, or $Rec\_Ratio_{i,t-1}$.

Finally, we also explore the effects of firm waste on loan covenant requirements. Given that *Covenant* is a dummy variable, we use a probit model to assess the probability of a loan imposing higher covenants on firms with poorer waste management practices. This probit model is represented by:

$$\Pr\left(Covenant_{i,t} = 1 \mid Waste_{i,t-1}, X_{i,t-1}, Z_{i,t}\right) = \Phi\left(\beta_0 + \beta_1 Waste_{i,t-1} + \theta' X_{i,t-1} + \delta' Z_{i,t} + \gamma_i + \gamma_t\right) \quad (4)$$

Where $\Phi(.)$ represents the cumulative standard normal distribution function, and $Covenant_{i,t}$ is a dummy variable equal to one if the loan syndicate contains covenant requirements, and zero otherwise.

[Insert Table 12 here]

Table 12 presents the analysis of nonprice loan contractual features. Ultimately, we find insufficient evidence to suggest that banks consider firms' waste management practices in their nonprice loan characteristics. While the signs in columns (2)–(8) are intuitively plausible, and therefore imply that higher waste intensities (recycling rates) decrease (increase) loan maturity and size, the only result that is significant and plausible is the negative coefficient of *Waste/Sales* on *Ln(Size)*. This indicates that banks may provide smaller loans to firms with higher waste intensities relative to those with lower waste intensities. However, there is ultimately little evidence to suggest that banks incorporate firms' waste management practices into their loan nonprice decisions.

Overall, these findings contrast to prior studies exploring the effect of poor environmental performance on nonprice loan terms, which typically find negative relations with maturity and size (e.g., He et al., 2021; Ho & Wong, 2023; Javadi & Masum, 2021; Nandy & Lodh, 2012). Hence, this may prompt policymakers to extend the scope of waste management considerations in lending frameworks to include other loan contractual features, in addition to prices.

6. Conclusion

Global waste generation is an escalating problem driven by population growth, large-scale urbanisation, and industrialisation. As these factors intensify, so does the need to improve waste management. Banks, by allocating credit to firms with superior waste management practices, can play a leading role in addressing this impending challenge. While bank loan prices have already been found to reflect firms' environmental performance, previous literature has not revealed whether this is also the case for firms' waste management practices. The purpose of this study therefore was to examine how the private sector internalises waste externalities by investigating the extent to which banks incorporate firms' waste management practices into their loan pricing decisions.

To address this research question, we employed a sample of 1,636 syndicated loans to 268 public U.S. companies between 2010 and 2023. Using an OLS regression with firm-, loan- and macro-level controls, as well as firm and year fixed effects, we find a significantly positive association between waste generation and bank loan spreads, suggesting that banks penalise firms with poor waste management practices with higher financing costs. This finding is robust to different combinations of fixed effects, alternative measures of waste, including its subcomponents (i.e., hazardous and non-hazardous), and alternative measures of loan pricing. Through these robustness tests, we also find evidence to suggest that banks reward firms with superior recycling practices with cheaper loan costs, a relationship that was initially insignificant in our baseline results.

Furthermore, we find that this positive relation between firm waste and loan costs is more discernible for firms with higher risk, weaker corporate governance, and less preferable ESG traits. Finally, we address potential endogeneity in our findings through an instrumental variable 2SLS approach and propensity score matching.

Overall, the findings can be evaluated broadly in terms of their contribution. From an academic perspective, the results contribute to the extant literature in two ways. First, they provide new evidence on the impact of corporate environmental performance on firms' cost of capital. Second, they highlight the financial implications of firms' waste management practices. These are important aspects of sustainable finance that require ongoing research to ensure the effective transfer of findings to the private sector.

Furthermore, our findings present important propositions for policymakers and practitioners. For policymakers, the results highlight the significant role that financial institutions play in funding ethical business practices, emphasising the need for regulations requiring banks to integrate ESG metrics like waste management into their lending frameworks. Especially, our findings indicate that new policies may be necessary to further encourage banks to integrate firms' recycling practices into their loan pricing decisions, ensuring the transition to a circular economy. Additionally, the results highlight the need for firms to accurately disclose their pollution levels, including waste generation, to enable banks to properly assess borrowers' environmental externalities. Thus, policymakers should consider mandating or improving environmental disclosure transparency.

Finally, the results are also relevant for practitioners and managers to understand the factors driving their loan financing costs. Especially, firms can benefit from lower costs of capital by implementing greater waste management practices, particularly if they have low risk, stronger corporate governance, and more preferable ESG traits.

However, while the results are intuitively plausible and consistent with our hypotheses, it should be acknowledged that they may be subject to several limitations. Firstly, the waste data sourced from Refinitiv covers large, public companies, and thus our sample excludes private and small to medium-sized enterprises. This limitation may affect the generalisability of the findings to these groups, as their financial constraints and waste management practices may differ from those of large public companies. Additionally, due to limited disclosure requirements for firm-level waste, the data may provide an inaccurate overview of firms' waste management practices. For instance, although the data offers hazardous and non-hazardous waste subcomponents, the composition of waste is far more complex and can be further categorised (e.g., into organic waste, plastics, metals, etc.). Given that waste composition varies significantly between economic contexts – for example, in higher-income economies, consumed goods contain more plastic and paper, while the proportion of organic waste is lower (Kaza et al., 2018) – the generalisability of the findings to lower-income economies may be limited.

Considering these limitations, there are several opportunities for future research to extend our analysis. Specifically, further research exploring different data samples or other aspects of ESG in lending decisions across more recent time periods will continue to satisfy the ongoing need for up-to-date research required by policymakers and practitioners. Furthermore, while we examined the cross-sectional heterogeneity of borrowers in this study, further exploration into the heterogeneity of lenders could also provide valuable insights. For example, exploring how the 'greenness' of banks affects lending decisions would enhance the findings and contribute to the ongoing debate investigating whether ‘green’ banks are more likely to integrate environmental factors into their lending decisions, particularly in relation to firm waste.

Finally, while our robustness and endogeneity tests help mitigate issues such as omitted variables, self-selection bias, and reverse causality, they have limitations and may not fully eliminate endogeneity risks. Thus, future research could benefit from examining an exogenous shock to firms’ waste management practices to further address endogeneity concerns. Analysing such a shock would provide a natural experiment that better isolates causal effects, contributing to more valid and generalisable conclusions.

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Appendix

Table A1: Sample Selection

Data source	Observations
LPC DealScan for loans to public U.S. firms from 2010 to 2023	185,382
Less duplicates	(164,569)
Less missing loan characteristics (i.e., AISD, maturity, size)	(2,411)
Less merging with Compustat NA CUSIPs	(6,646)
Less merging with Refinitiv ESG, Eikon Screener and Worldscope data	(3,135)
Less missing firm waste generation	(6,804)
Less missing baseline analysis controls (i.e., assets, leverage, MTB, tangibility, profitability, share price volatility)	(156)
Less GICS financials	(25)
Final sample for the period from 2010 to 2023	**1,636**

This table provides an overview of the data sample selection process. The final sample includes 1,636 observations for the period 2010 to 2023.

Table A2: Variable Definitions and Sources

Variable	Definition	Source
Dependent variables		
Ln(Spread)	The natural logarithm of the all-in spread drawn rate, representing the amount, in terms of basis points, that a borrower pays over LIBOR or LIBOR equivalent for each dollar drawn down	DealScan
Ln(Fees)	The natural logarithm of the fees included in a loan contract, including the commitment fee, upfront fee, cancellation fee, and utilisation fee	DealScan; Berg et al. (2016) and Ehlers et al. (2022)
Ln(TCB)	The natural logarithm of the total borrowing costs (TCB), where TCB equals the sum of the all-in-spread-drawn plus other fees (as defined above) in the loan contract	DealScan; Berg et al. (2016) and Ehlers et al. (2022)
Independent variables		
Waste	The natural logarithm of the total solid waste produced by a firm and disposed to landfill, in tonnes	Refinitiv ESG
Waste/Sales	The ratio of a firm's total waste produced to its net sales	Refinitiv ESG and Worldscope
Waste/Assets	The ratio of a firm's total waste produced to its total assets	Refinitiv ESG and Worldscope
Rec_Ratio	The ratio of the quantity of waste that is recycled by a firm to its total waste generated	Refinitiv ESG
H_Waste	The natural logarithm of the total hazardous waste produced by a firm in tonnes	Refinitiv ESG
NH_Waste	The natural logarithm of the total non-hazardous waste produced by a firm in tonnes	Refinitiv ESG
Loan characteristics		
Ln(Maturity)	The natural logarithm of the loan maturity in months	DealScan
Ln(Size)	The natural logarithm of the loan amount in USD $ millions	DealScan
Covenant	Dummy variable that is equal to one if the loan includes covenants, and zero otherwise	DealScan
Performance	Dummy variable that is equal to one if the loan includes performance pricing, and zero otherwise	DealScan
Collateral	Dummy variable that is equal to one if the loan is secured with collateral, and zero otherwise	DealScan
Lead Arrangers	The total number of lead arrangers present in the loan syndicate	DealScan
Firm characteristics		
Ln(Assets)	The natural logarithm of a firm's total assets in USD $ millions	Worldscope
Leverage	The ratio of a firm's short-term debt plus long-term debt to its total assets	Worldscope
MTB	The market-to-book ratio of a firm's market value of common equity to its balance sheet value of common equity	Datastream
Tangibility	The ratio of a firm's net property, plant and equipment to its total assets	Worldscope
Profitability	The ratio of a firm's EBITDA (calculated as pre-tax income + interest expense on debt + depreciation,	Worldscope

	depletion and amortization ─ interest capitalised) to total assets	
Shareprice_vol	A measure of a firm's average share price movement to a high and low from a mean price for each year	Worldscope
Macroeconomic characteristics		
Credit spread	The difference in yields between a U.S. AAA corporate bond and a BAA corporate bond	Datastream
Term spread	The difference in yields between a 10-year Treasury bond and a 2-year Treasury bond	Datastream
Risk variables		
Z-score	A firm's Z-score with manufacturing weights, computed as (1.2 × working capital / total assets) + (1.4 × retained earnings / total assets) + (3.3 × EBIT / total assets) + (0.6 × market capitalisation / total liabilities) + (1.0 × asset turnover ratio)	Eikon Screener
PD	A forward-looking point-in-time probability of default measure, calculated over a 12-month horizon	Credit Risk Initiative, National University of Singapore[9]
Beta	A firm's historical market beta, representing its systematic risk relative to the market	Datastream
Governance variables		
Independent	The percentage of independent board members at a firm	Refinitiv ESG
Busy	The average number of other firm affiliations for each board member	Refinitiv ESG
Board size	The total number of board members for the firm at the end of the fiscal year	Refinitiv ESG
Duality	Dummy variable equal to one if the CEO is concurrently chairman of the board, and zero otherwise	Eikon Screener
Ln(Exec_comp)	The natural logarithm of the total compensation paid to all senior executives of a firm	Eikon Screener
Attendance	The average attendance percentage of board meetings	Refinitiv ESG
Governance	A variable predicting corporate governance that is based on the first principal component from a PCA of other corporate governance variables (i.e., the same variables used in Chen et al. (2021), including *Independent*, *Busy*, *Board Size*, *Duality*, *Ln(Exec Comp)*, and *Attend*)	Chen et al. (2021)
Board diversity	The percentage of females on the board of the firm	Refinitiv ESG
CSR Committee	Dummy variable that is equal to one if the firm has a CSR committee or team, and zero otherwise	Eikon Screener
CSR Compensation	Dummy variable equal to one if the senior executive's compensation is linked to CSR, health and safety or sustainability targets, and zero otherwise	Eikon Screener
Preference variables		
Politic	Dummy variable equal to one if a borrowing firm is headquartered in a Republican state, and zero if headquartered in a Democratic state	Pew Research Centre[10]
ESG_score	A company score based on the self-reported environmental, social and governance information	Refinitiv ESG

This table presents an overview of the variables used throughout the study, including their definitions and sources.

[9] https://nuscri.org/en/ourdata/
[10] https://www.pewresearch.org/religious-landscape-study/database/compare/party-affiliation/by/state/

Table 1: Distribution by GICS Industry

GICS Industry	Frequency	Percent	Cumulative %
Aerospace & Defense	38	2.32	2.32
Air Freight & Logistics	20	1.22	3.55
Automobile Components	5	0.31	3.85
Automobiles	87	5.32	9.17
Beverages	19	1.16	10.33
Biotechnology	14	0.86	11.19
Broadline Retail	9	0.55	11.74
Building Products	45	2.75	14.49
Chemicals	102	6.23	20.72
Commercial Services & Supplies	8	0.49	21.21
Communications Equipment	14	0.86	22.07
Construction & Engineering	3	0.18	22.25
Construction Materials	3	0.18	22.43
Consumer Staples Distribution & Retail	17	1.04	23.47
Containers & Packaging	42	2.57	26.04
Diversified Consumer Services	1	0.06	26.10
Diversified Telecommunication Services	29	1.77	27.87
Electric Utilities	81	4.95	32.82
Electrical Equipment	12	0.73	33.56
Electronic Equipment, Instruments & Components	37	2.26	35.82
Energy Equipment & Services	9	0.55	36.37
Entertainment	9	0.55	36.92
Food Products	89	5.44	42.36
Ground Transportation	17	1.04	43.40
Health Care Equipment & Supplies	80	4.89	48.29
Health Care Providers & Services	39	2.38	50.67
Health Care REITs	6	0.37	51.04
Hotel & Resort REITs	20	1.22	52.26
Hotels, Restaurants & Leisure	99	6.05	58.31
Household Durables	21	1.28	59.60
Household Products	32	1.96	61.55
IT Services	24	1.47	63.02
Independent Power and Renewable Electricity Producers	13	0.79	63.81
Industrial Conglomerates	9	0.55	64.36
Interactive Media & Services	2	0.12	64.49
Leisure Products	21	1.28	65.77
Life Sciences Tools & Services	24	1.47	67.24
Machinery	74	4.52	71.76
Metals & Mining	33	2.02	73.78
Multi-Utilities	53	3.24	77.02
Office REITs	13	0.79	77.81
Oil, Gas & Consumable Fuels	44	2.69	80.50
Passenger Airlines	37	2.26	82.76
Pharmaceuticals & Personal Care Products	53	3.24	86.00
Professional Services	10	0.61	86.61
Residential & Retail REITs	10	0.61	87.22
Semiconductors & Semiconductor Equipment	46	2.81	90.04
Software	24	1.47	91.50
Specialized REITs	16	0.98	92.48
Specialty Retail	21	1.28	93.77
Technology Hardware, Storage & Peripherals	17	1.04	94.80
Textiles, Apparel & Luxury Goods	49	3.00	97.80
Tobacco	20	1.22	99.02
Trading Companies & Distributors	14	0.86	99.88
Water Utilities	2	0.12	100.00
Total	1,636	100.00	

This table presents a breakdown of the distribution of observations by GICS industry. A total of 1,636 observations were recorded between 2010 and 2023 for 268 unique firms.

Table 2: Descriptive Statistics

Variables	N	Mean	SD	Min	p25	Median	p75	Max
Ln(Spread)	1636	4.855	0.474	2.862	4.605	4.828	5.075	6.215
Waste/Assets	1636	0.172	0.751	0.000	0.007	0.031	0.107	17.315
Waste/Sales	1636	0.368	2.222	0.000	0.012	0.045	0.141	57.538
Rec_Ratio	1379	0.575	0.268	0.001	0.398	0.601	0.810	0.987
Waste	1636	10.932	2.045	5.226	9.547	11.104	12.194	15.718
H_Waste	1057	7.761	2.584	0.000	6.184	7.879	9.788	12.972
NH_Waste	1105	10.716	2.175	4.067	9.629	10.816	12.053	15.718
Ln(Maturity)	1636	3.579	0.678	1.792	3.178	3.871	4.094	4.431
Ln(Size)	1636	6.984	1.083	3.807	6.215	6.908	7.719	9.393
Covenant	1636	0.441	0.497	0.000	0.000	0.000	1.000	1.000
Performance	1636	0.336	0.472	0.000	0.000	0.000	1.000	1.000
Collateral	1636	0.139	0.346	0.000	0.000	0.000	0.000	1.000
Lead Arrangers	1636	5.382	3.989	0.000	3.000	4.000	7.000	26.000
Ln(Fees)	800	2.806	1.008	-0.288	2.197	2.708	3.314	5.298
Ln(TCB)	1636	4.925	0.510	2.862	4.691	4.905	5.165	6.477
Ln(Assets)	1636	9.943	1.340	7.190	8.951	9.967	10.816	12.906
Leverage	1636	0.343	0.156	0.021	0.237	0.316	0.433	0.717
MTB	1636	2.506	14.363	-108.720	1.540	2.430	4.160	51.320
Tangibility	1636	0.336	0.251	0.017	0.133	0.244	0.535	0.933
Profitability	1636	0.122	0.072	-0.318	0.082	0.109	0.164	0.420
Shareprice_Vol	1636	0.242	0.087	0.114	0.173	0.226	0.299	0.495
Credit Spread	1636	0.985	0.158	0.680	0.900	1.000	1.090	1.250
Term Spread	1636	0.921	0.927	-0.620	0.170	0.930	1.520	2.510
Z-score	1619	2.837	2.169	0.215	1.320	2.444	3.690	14.454
Probability of Default	1242	0.002	0.007	0.000	0.000	0.000	0.001	0.050
Beta	1636	1.231	0.754	-0.086	0.652	1.084	1.664	3.398
Independent	1635	0.852	0.074	0.611	0.800	0.867	0.917	0.938
Board Busy	1636	0.985	0.471	0.130	0.690	0.920	1.270	2.670
Board Size	1636	11.512	2.143	4.000	10.000	11.000	13.000	18.000
Duality	1636	0.531	0.499	0.000	0.000	1.000	1.000	1.000
Ln(Exec_Comp)	1635	17.196	0.577	15.569	16.783	17.229	17.615	18.434
Attendance	1600	0.802	0.090	0.750	0.750	0.750	0.830	1.000
Diversity	1636	0.236	0.099	0.000	0.167	0.222	0.300	0.500
CSR Committee	1636	0.877	0.329	0.000	1.000	1.000	1.000	1.000
CSR Compensation	1636	0.499	0.500	0.000	0.000	0.000	1.000	1.000
Governance	1599	0.005	1.223	-4.015	-0.773	0.114	0.887	3.023
Political Dummy	1636	0.196	0.397	0.000	0.000	0.000	0.000	1.000
ESG Score	1636	0.677	0.129	0.338	0.599	0.698	0.773	0.911

This table presents the descriptive statistics of the analysis for the period 2010 to 2023. Variable definitions and their sources can be viewed in Table A2. All continuous variables are winsorised at the 1st and 99th percentiles to mitigate outliers. “p25” and “p75” denote the 25th and 75th percentiles, respectively.

Table 3: Baseline Regression of Waste Effects on Bank Loan Spreads

Variables	(1) Ln(Spread)	(2) Ln(Spread)	(3) Ln(Spread)	(4) Ln(Spread)	(5) Ln(Spread)	(6) Ln(Spread)	(7) Ln(Spread)	(8) Ln(Spread)	(9) Ln(Spread)
Waste/Sales	0.0956***	0.0768***	0.0758***						
	(5.85)	(3.45)	(3.43)						
Waste/Assets				0.2156***	0.1893***	0.1889***			
				(4.87)	(3.43)	(3.36)			
Rec_Ratio							-0.0766	-0.0499	-0.0505
							(-0.72)	(-0.50)	(-0.51)
Ln(Assets)		-0.1177**	-0.1174**		-0.1176**	-0.1175**		-0.1426**	-0.1313**
		(-2.33)	(-2.32)		(-2.33)	(-2.32)		(-2.35)	(-2.16)
Leverage		0.3636	0.3516		0.3799*	0.3670*		0.4770*	0.4822*
		(1.56)	(1.55)		(1.67)	(1.66)		(1.76)	(1.84)
MTB		0.0025*	0.0026*		0.0026*	0.0026*		0.0012	0.0012
		(1.92)	(1.91)		(1.96)	(1.95)		(0.99)	(1.04)
Tangibility		-0.2172	-0.2378		-0.1622	-0.1820		-0.4024	-0.4392
		(-0.71)	(-0.78)		(-0.55)	(-0.61)		(-1.11)	(-1.22)
Profitability		-0.3239	-0.3425		-0.3465	-0.3666		-0.2114	-0.1505
		(-1.01)	(-1.06)		(-1.06)	(-1.12)		(-0.60)	(-0.42)
Shareprice_vol		0.8508	0.6919		0.8778	0.7276		1.1027	0.9824
		(1.54)	(1.23)		(1.63)	(1.33)		(1.43)	(1.22)
Ln(Maturity)			0.0406			0.0431			0.0491*
			(1.31)			(1.38)			(1.65)
Ln(Size)			-0.0057			-0.0061			-0.0184
			(-0.40)			(-0.43)			(-1.08)
Covenant			0.0001			-0.0027			0.0185
			(0.00)			(-0.12)			(0.68)
Performance			0.0228			0.0225			0.0060
			(1.05)			(1.05)			(0.26)
Collateral			0.0759			0.0736			0.0472
			(1.11)			(1.08)			(0.73)
Lead Arrangers			-0.0002			-0.0002			0.0051
			(-0.03)			(-0.02)			(0.79)
Credit Spread			0.6038			0.6134			0.2573
			(1.36)			(1.39)			(0.51)
Term Spread			0.0122			0.0113			0.0168
			(0.31)			(0.29)			(0.34)
Constant	5.0427***	5.9990***	5.2295***	5.1248***	5.9851***	5.2009***	5.5153***	6.5770***	6.0988***
	(36.53)	(7.79)	(5.73)	(37.03)	(7.71)	(5.64)	(38.31)	(7.44)	(5.70)
Observations	1,636	1,636	1,636	1,636	1,636	1,636	1,379	1,379	1,379
R-squared	0.781	0.789	0.791	0.781	0.790	0.792	0.793	0.801	0.804
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results for the baseline regression investigating the effects of a firm's waste management practices on its bank loan spreads. The results are found through the OLS regression: $Ln(Spread)_{i,t} = \beta_0 + \beta_1 Waste_{i,t-1} + \theta' X_{i,t-1} + \delta' Z_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t}$, where $Ln(Spread)_{i,t}$denotes the natural logarithm of the all-in-spread-drawn for loan i in year t; $Waste_{i,t-1}$ denotes a firm's waste management practices, proxied by $Waste/Sales_{i,t-1}$ in columns (1)–(3), $Waste/Assets_{i,t-1}$ in columns (4)–(6), and $Rec\_Ratio_{i,t-1}$ in columns (7)–(9). $X_{i,t-1}$ represents a vector of firm-level controls, and $Z_{i,t}$ denotes loan- and macro-level controls. γ_i and γ_t represent firm and year fixed effects, and $\epsilon_{i,t}$ represents the error term of the regression. Variable definitions are provided in Table A2. T-statistics are reported in parentheses and standard errors are clustered at the firm-level.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. For brevity, coefficients on fixed effects are not reported.

Table 4: Baseline Robustness to Alternative Fixed Effects

Variables	(1) Ln(Spread)	(2) Ln(Spread)	(3) Ln(Spread)
Panel A: Waste/Sales			
Waste/Sales	0.0777***	0.0038	0.0055**
	(3.22)	(1.12)	(2.27)
Constant	5.7512***	5.1789***	4.4566***
	(5.48)	(9.79)	(9.82)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	No	No
Industry FE	No	Yes	No
Loan type	No	No	Yes
Loan purpose	No	No	Yes
Observations	1,636	1,636	1,636
R-squared	0.762	0.561	0.540
	(1) Ln(Spread)	(2) Ln(Spread)	(3) Ln(Spread)
Panel B: Waste/Assets			
Waste/Assets	0.2003***	0.0166	0.0181**
	(3.08)	(1.30)	(2.19)
Constant	5.7141***	5.1722***	4.4578***
	(5.41)	(9.81)	(9.84)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	No	No
Industry FE	No	Yes	No
Loan purpose	No	No	Yes
Loan type	No	No	Yes
Observations	1,636	1,636	1,636
R-squared	0.763	0.561	0.540
	(1) Ln(Spread)	(2) Ln(Spread)	(3) Ln(Spread)
Panel C: Rec_Ratio			
Rec_Ratio	-0.0235	-0.1888***	-0.1658***
	(-0.21)	(-2.80)	(-2.73)
Constant	6.9147***	5.2935***	4.3357***
	(5.63)	(8.18)	(7.76)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	No	No
Industry FE	No	Yes	No
Loan purpose	No	No	Yes
Loan type	No	No	Yes
Observations	1,379	1,379	1,379
R-squared	0.771	0.570	0.563

This table presents the robustness test using different combinations of fixed effects. Panel A explores the effects of *Waste/Sales* on *Ln(Spread)*, while Panel B examines *Waste/Assets* and Panel C explores *Rec_Ratio*. Column (1) utilises firm and year fixed effects. Column (2) utilises industry and year fixed effects. Column (3) utilises loan and year fixed effects. Variable definitions are provided in Table A2. T-statistics are reported in parentheses and standard errors are clustered at the firm-level.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. For brevity, coefficients on control variables and fixed effects are not reported.

Table 5: Effects of Absolute, Hazardous and Non-Hazardous Waste on Loan Spreads

Variables	(1) Ln(Spread)	(2) Ln(Spread)	(3) Ln(Spread)
Waste	0.0775***		
	(3.83)		
NH_Waste		0.0669***	
		(3.38)	
H_Waste			0.0065
			(0.33)
Constant	5.4602***	5.6569***	5.3175***
	(6.25)	(5.82)	(4.94)
Control for			
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan type	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes
R-squared	0.794	0.804	0.797
Observations	1,636	1,105	1,057

This table presents the robustness tests for the absolute values of waste, including its subcomponents (hazardous waste and non-hazardous waste). Column (1) presents the effects of firm's total waste, column (2) presents the effects of non-hazardous waste, while column (3) presents the effects of hazardous waste. Loan, year and firm fixed effects are included. Variable definitions are provided in Table A2. T-statistics are reported in parentheses and standard errors are clustered at the firm-level.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. For brevity, coefficients on control variables and fixed effects are not reported.

Table 6: Risk Channel Subsample Analysis

Variables	Z-Score		PD		Beta	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)
Panel A: Waste/Sales						
Waste/Sales	0.0050**	-0.0223	0.0054	0.0060**	0.0323	0.0049**
	(2.22)	(-0.59)	(0.34)	(2.18)	(1.50)	(2.39)
Ln(Assets)	-0.0168	-0.1059***	-0.0232	-0.0361**	-0.0735***	-0.0137
	(-1.14)	(-3.54)	(-0.88)	(-2.54)	(-3.12)	(-0.72)
Leverage	-0.0336	0.1747	0.2845	0.0410	0.1025	0.2028*
	(-0.22)	(0.65)	(1.36)	(0.22)	(0.39)	(1.74)
MTB	-0.0035***	-0.0002	0.0005	-0.0030***	-0.0009	-0.0006
	(-4.42)	(-0.18)	(0.42)	(-4.38)	(-0.87)	(-0.41)
Tangibility	0.2600***	0.3972**	0.2691***	0.2684***	0.2100*	0.2992***
	(5.18)	(2.50)	(2.78)	(3.95)	(1.91)	(4.54)
Profitability	-0.3341	-1.6173***	-1.1499***	-1.4040***	-1.8024***	-0.9692***
	(-1.10)	(-3.54)	(-3.45)	(-2.69)	(-3.52)	(-3.49)
Shareprice_Vol	1.4476***	1.4403***	1.4842***	1.4368***	1.5273***	1.3057***
	(5.69)	(3.62)	(3.03)	(4.33)	(3.77)	(3.86)
Ln(Maturity)	0.0550	0.0393	0.0902*	0.0257	0.1027**	-0.0618
	(1.40)	(0.91)	(1.67)	(0.64)	(2.43)	(-1.60)
Ln(Size)	-0.0327**	-0.0375	-0.0524*	-0.0420***	-0.0408	-0.0461***
	(-2.49)	(-1.10)	(-1.96)	(-2.83)	(-1.46)	(-2.86)
Covenant	-0.0373	0.0663*	0.0596	-0.0049	0.0489	-0.0050
	(-1.19)	(1.73)	(1.44)	(-0.15)	(1.28)	(-0.15)
Performance	0.0536*	0.0290	0.0170	0.0782**	0.0547	0.0319
	(1.90)	(0.83)	(0.50)	(2.36)	(1.55)	(1.00)
Collateral	0.2266***	0.1924***	0.2312	0.2048***	0.2912***	0.2024***
	(3.33)	(2.94)	(1.60)	(3.14)	(3.34)	(3.33)
Lead Arrangers	0.0166***	0.0094	0.0192**	0.0186***	0.0108	0.0171***
	(2.78)	(0.68)	(2.08)	(3.32)	(0.87)	(3.30)
Credit Spread	0.5227	0.6710	-0.1055	0.9197*	0.4507	0.2426
	(0.96)	(1.08)	(-0.14)	(1.90)	(0.87)	(0.42)
Term Spread	-0.0410	-0.0762	-0.0269	-0.0776**	0.0042	-0.0822
	(-0.93)	(-1.36)	(-1.00)	(-2.12)	(0.13)	(-1.58)
Constant	4.1569***	4.8593***	4.8409***	3.9798***	4.8261***	4.6757***
	(6.52)	(7.35)	(5.63)	(7.47)	(7.87)	(7.90)
Observations	815	832	621	1,015	818	818
R-squared	0.592	0.484	0.451	0.524	0.511	0.578
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Loan type	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)
Panel B: Waste/Assets						
Waste/Assets	0.0185**	-0.0260	0.0105	0.0185**	0.1410*	0.0134*
	(2.26)	(-0.51)	(0.44)	(2.09)	(1.90)	(1.76)
Ln(Assets)	-0.0162	-0.1061***	-0.0228	-0.0357**	-0.0702***	-0.0132
	(-1.09)	(-3.55)	(-0.86)	(-2.51)	(-3.07)	(-0.69)
Leverage	-0.0341	0.1746	0.2849	0.0400	0.0985	0.2002*
	(-0.23)	(0.65)	(1.37)	(0.22)	(0.38)	(1.72)
MTB	-0.0034***	-0.0002	0.0005	-0.0030***	-0.0009	-0.0006
	(-4.43)	(-0.18)	(0.41)	(-4.36)	(-0.92)	(-0.40)

Tangibility	0.2578***	0.3972**	0.2714***	0.2676***	0.2050*	0.2987***
	(5.17)	(2.51)	(2.75)	(3.94)	(1.84)	(4.54)
Profitability	-0.3425	-1.6131***	-1.1571***	-1.4018***	-1.8397***	-0.9696***
	(-1.13)	(-3.54)	(-3.49)	(-2.68)	(-3.56)	(-3.49)
Shareprice_Vol	1.4304***	1.4368***	1.4746***	1.4342***	1.4965***	1.3122***
	(5.62)	(3.62)	(2.96)	(4.32)	(3.76)	(3.89)
Ln(Maturity)	0.0548	0.0395	0.0897*	0.0254	0.0968**	-0.0619
	(1.40)	(0.92)	(1.66)	(0.63)	(2.31)	(-1.60)
Ln(Size)	-0.0331**	-0.0376	-0.0528*	-0.0423***	-0.0426	-0.0465***
	(-2.52)	(-1.11)	(-1.96)	(-2.85)	(-1.57)	(-2.88)
Covenant	-0.0378	0.0668*	0.0594	-0.0050	0.0481	-0.0048
	(-1.21)	(1.73)	(1.43)	(-0.15)	(1.26)	(-0.14)
Performance	0.0532*	0.0289	0.0172	0.0777**	0.0550	0.0313
	(1.88)	(0.83)	(0.50)	(2.34)	(1.57)	(0.98)
Collateral	0.2299***	0.1925***	0.2327	0.2061***	0.2949***	0.2037***
	(3.37)	(2.94)	(1.60)	(3.16)	(3.37)	(3.34)
Lead Arrangers	0.0166***	0.0093	0.0193**	0.0186***	0.0116	0.0170***
	(2.79)	(0.67)	(2.09)	(3.31)	(0.94)	(3.28)
Credit Spread	0.5295	0.6742	-0.1101	0.9139*	0.4323	0.2285
	(0.97)	(1.09)	(-0.15)	(1.89)	(0.83)	(0.40)
Term Spread	-0.0414	-0.0761	-0.0271	-0.0779**	0.0036	-0.0825
	(-0.95)	(-1.36)	(-1.02)	(-2.13)	(0.11)	(-1.58)
Constant	4.1507***	4.8588***	4.8475***	3.9842***	4.8377***	4.6874***
	(6.52)	(7.35)	(5.64)	(7.49)	(7.90)	(7.94)
Observations	815	832	621	1,015	818	818
R-squared	0.592	0.484	0.451	0.524	0.512	0.577
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Loan type	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the exploration of a risk channel in driving the relationship between firm waste and loan spreads. Models (1)–(2) explore the role of firms' Z-scores. Models (3)-(4) explore firms' probability of default. Models (5)–(6) explore the effect of firms' beta. Loan and year fixed effects are included. Variable definitions are provided in Table A2. T-statistics are reported in parentheses and standard errors are clustered at the firm-level.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. For brevity, coefficients on fixed effects are not reported.

Table 7: Governance Channel Subsample Analysis

Variables	Independence		Busy		Board Size		Duality		Exec Comp		Attendance		Governance	
	Low	High	Low	High	Low	High	Yes	No	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(19)	(20)
	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)
Panel A: Waste/Sales														
Waste/Sales	-0.0354	0.0055**	0.0047**	0.0064	0.0034	0.0027	0.0132	0.0011	0.0065***	0.0171	0.0134	0.0040	0.0072***	0.0045
	(-1.41)	(2.09)	(2.07)	(0.60)	(1.10)	(0.28)	(0.88)	(0.45)	(3.31)	(0.99)	(0.84)	(1.32)	(3.02)	(0.23)
Ln(Assets)	-0.0463**	-0.0281	-0.0367***	-0.0271	-0.0560**	-0.0553***	-0.0642***	-0.0193	-0.0292	0.0250	-0.0495***	0.0011	-0.0213	-0.0425**
	(-2.48)	(-1.52)	(-2.68)	(-1.23)	(-2.40)	(-3.28)	(-2.82)	(-1.21)	(-1.62)	(0.96)	(-3.22)	(0.04)	(-1.08)	(-2.05)
Leverage	-0.0394	0.3786***	-0.0149	0.1693	0.1950	0.1646	0.3439**	-0.0724	0.1378	0.0975	0.1241	0.1737	0.0748	0.2632
	(-0.18)	(2.70)	(-0.07)	(1.16)	(1.40)	(0.94)	(2.24)	(-0.37)	(1.23)	(0.42)	(0.65)	(1.06)	(0.71)	(1.19)
MTB	-0.0020	-0.0004	-0.0029***	-0.0011	-0.0012	-0.0020**	-0.0008	-0.0032**	-0.0015***	0.0004	-0.0012*	-0.0012	-0.0018**	0.0000
	(-1.07)	(-0.44)	(-2.79)	(-1.19)	(-1.23)	(-2.32)	(-1.00)	(-2.43)	(-2.66)	(0.22)	(-1.77)	(-0.47)	(-2.13)	(0.03)
Tangibility	0.3386***	0.1587**	0.1463**	0.3253***	0.2054**	0.2939***	0.2871***	0.2468***	0.1485**	0.3559***	0.2602***	0.1653	0.1889***	0.3007***
	(3.96)	(2.18)	(2.26)	(3.93)	(2.47)	(4.24)	(3.58)	(3.09)	(2.27)	(3.62)	(3.90)	(1.53)	(3.05)	(3.33)
Profitability	-1.5090***	-1.1099***	-1.8217**	-0.9824***	-1.1426***	-1.2068***	-1.2396***	-1.3745**	-0.9958***	-1.3747**	-1.2483***	-1.1569***	-0.6544***	-1.8238***
	(-2.67)	(-4.01)	(-2.49)	(-3.78)	(-2.90)	(-3.89)	(-4.28)	(-2.60)	(-4.05)	(-2.55)	(-2.61)	(-3.35)	(-3.02)	(-3.54)
Shareprice_Vol	1.6066***	1.9268***	1.3270***	1.5252***	1.9047***	1.2728***	1.0437***	2.1226***	1.0768***	2.3328***	1.4355***	1.6228***	1.2436***	1.6716***
	(4.48)	(5.92)	(4.50)	(4.25)	(6.02)	(5.20)	(3.95)	(6.82)	(4.61)	(6.18)	(4.91)	(3.02)	(5.07)	(4.24)
Ln(Maturity)	0.0430	0.0514	0.0438	0.0382	0.0467	0.0227	0.0247	0.0731	0.1030***	-0.0041	0.0334	0.0471	0.0943***	0.0061
	(0.97)	(1.14)	(0.87)	(1.11)	(1.57)	(0.55)	(0.61)	(1.57)	(3.37)	(-0.08)	(0.88)	(0.86)	(2.93)	(0.12)
Ln(Size)	-0.0438**	-0.0578***	-0.0232	-0.0881***	-0.0354	-0.0505***	-0.0369*	-0.0455**	-0.0309**	-0.0626**	-0.0331*	-0.1079***	-0.0318**	-0.0423*
	(-2.10)	(-3.11)	(-1.43)	(-3.98)	(-1.45)	(-2.75)	(-1.75)	(-2.08)	(-2.15)	(-2.43)	(-1.93)	(-3.95)	(-1.99)	(-1.83)
Covenant	-0.0278	0.0707**	-0.0679*	0.0871**	-0.0041	0.0163	-0.0012	0.0104	-0.0051	0.0222	0.0080	0.0438	-0.0249	0.0314
	(-0.70)	(2.39)	(-1.86)	(2.38)	(-0.14)	(0.48)	(-0.04)	(0.26)	(-0.17)	(0.58)	(0.25)	(1.00)	(-0.85)	(0.78)
Performance	0.1022***	0.0163	0.0374	0.0568	0.0069	0.0996***	0.0782**	0.0371	0.0084	0.0772**	0.0533*	0.0701	0.0069	0.1033***
	(2.62)	(0.50)	(1.19)	(1.56)	(0.24)	(2.97)	(2.38)	(1.24)	(0.25)	(2.32)	(1.84)	(1.57)	(0.25)	(2.83)
Collateral	0.2828***	0.0853	0.2244***	0.1988**	0.1996***	0.2904***	0.4257***	0.0684	0.2712***	0.2871***	0.2224***	0.3000**	0.2403***	0.3277***
	(4.35)	(0.98)	(3.22)	(2.16)	(2.71)	(3.71)	(4.98)	(1.14)	(4.14)	(3.12)	(3.14)	(2.33)	(4.67)	(3.51)
Lead Arrangers	0.0222***	0.0261***	0.0110	0.0273***	0.0021	0.0258***	0.0187***	0.0098	0.0160**	0.0144*	0.0187**	0.0152**	0.0169***	0.0132*
	(2.76)	(4.22)	(1.22)	(4.35)	(0.27)	(4.13)	(2.78)	(1.35)	(2.07)	(1.82)	(2.43)	(2.26)	(2.67)	(1.78)
Credit Spread	0.7624	0.5167	0.6478	0.4201	0.1171	0.6058	0.5398	1.0036**	0.1639	0.2785	0.7156	-0.1263	0.2758	1.0461**
	(1.29)	(0.83)	(1.12)	(0.68)	(0.20)	(1.24)	(0.83)	(2.03)	(0.26)	(0.52)	(1.37)	(-0.17)	(0.45)	(2.09)
Term Spread	-0.0116	-0.0961*	-0.0292	-0.0691	-0.0545	-0.0470	-0.0525	0.0018	-0.0096	-0.0971*	-0.0219	-0.1357*	-0.0556	-0.0219
	(-0.30)	(-1.85)	(-0.76)	(-1.23)	(-1.00)	(-1.41)	(-1.11)	(0.06)	(-0.28)	(-1.76)	(-0.61)	(-1.88)	(-1.24)	(-0.56)
Constant	4.1561***	4.1868***	4.3577***	4.5324***	4.9108***	4.5766***	4.5850***	3.6775***	4.5726***	4.0238***	4.1621***	5.3464***	4.3524***	4.0263***
	(6.23)	(6.35)	(6.75)	(6.69)	(7.93)	(8.32)	(6.11)	(6.91)	(6.74)	(6.73)	(7.19)	(6.18)	(6.83)	(6.54)
Observations	841	832	821	860	838	1,084	869	767	818	819	1,171	465	801	838
R-squared	0.600	0.499	0.494	0.601	0.548	0.575	0.557	0.545	0.548	0.553	0.530	0.619	0.478	0.580
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Loan type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(19)	(20)
	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)
Panel B: Waste/Assets														
Waste/Assets	-0.0095	0.0164*	0.0130	0.0147	0.0113	0.0148	0.0490	0.0019	0.0210***	0.0558	0.0202	0.0197	0.0224***	0.0789
	(-0.16)	(1.88)	(1.47)	(0.67)	(1.07)	(0.78)	(1.10)	(0.21)	(2.72)	(1.14)	(0.66)	(1.41)	(2.64)	(0.91)
Ln(Assets)	-0.0452**	-0.0273	-0.0362***	-0.0265	-0.0557**	-0.0546***	-0.0626***	-0.0193	-0.0279	0.0269	-0.0486***	0.0021	-0.0202	-0.0412**
	(-2.36)	(-1.48)	(-2.63)	(-1.20)	(-2.38)	(-3.19)	(-2.75)	(-1.21)	(-1.53)	(1.04)	(-3.15)	(0.08)	(-1.02)	(-1.99)
Leverage	-0.0429	0.3769***	-0.0160	0.1701	0.1949	0.1616	0.3449**	-0.0723	0.1350	0.0981	0.1275	0.1796	0.0726	0.2598
	(-0.20)	(2.69)	(-0.07)	(1.17)	(1.39)	(0.92)	(2.25)	(-0.37)	(1.20)	(0.42)	(0.67)	(1.09)	(0.69)	(1.17)
MTB	-0.0020	-0.0004	-0.0029***	-0.0011	-0.0012	-0.0020**	-0.0008	-0.0032**	-0.0015***	0.0003	-0.0012*	-0.0012	-0.0017**	0.0000
	(-1.05)	(-0.45)	(-2.78)	(-1.20)	(-1.22)	(-2.33)	(-1.00)	(-2.43)	(-2.65)	(0.21)	(-1.77)	(-0.46)	(-2.11)	(0.01)
Tangibility	0.3251***	0.1579**	0.1482**	0.3253***	0.2034**	0.2911***	0.2902***	0.2480***	0.1452**	0.3560***	0.2671***	0.1569	0.1864***	0.2894***
	(3.86)	(2.15)	(2.29)	(3.97)	(2.43)	(4.24)	(3.66)	(3.06)	(2.19)	(3.72)	(3.99)	(1.46)	(2.99)	(3.28)
Profitability	-1.4788***	-1.1138***	-1.8223**	-0.9866***	-1.1404***	-1.2080***	-1.2478***	-1.3751**	-0.9943***	-1.3914**	-1.2609***	-1.1638***	-0.6495***	-1.8406***
	(-2.62)	(-4.02)	(-2.49)	(-3.82)	(-2.89)	(-3.92)	(-4.35)	(-2.60)	(-4.06)	(-2.59)	(-2.64)	(-3.39)	(-3.00)	(-3.51)
Shareprice_Vol	1.6386***	1.9183***	1.3264***	1.5183***	1.8992***	1.2693***	1.0251***	2.1260***	1.0690***	2.3102***	1.4254***	1.5781***	1.2379***	1.6761***
	(4.60)	(5.84)	(4.48)	(4.20)	(5.98)	(5.15)	(3.98)	(6.83)	(4.56)	(6.09)	(4.88)	(2.89)	(5.06)	(4.31)
Ln(Maturity)	0.0445	0.0511	0.0437	0.0380	0.0466	0.0219	0.0240	0.0732	0.1028***	-0.0045	0.0334	0.0471	0.0939***	0.0044
	(1.00)	(1.14)	(0.87)	(1.10)	(1.57)	(0.53)	(0.59)	(1.57)	(3.37)	(-0.09)	(0.88)	(0.86)	(2.93)	(0.09)
Ln(Size)	-0.0443**	-0.0586***	-0.0234	-0.0886***	-0.0358	-0.0506***	-0.0373*	-0.0456**	-0.0315**	-0.0633**	-0.0335*	-0.1086***	-0.0327**	-0.0412*
	(-2.12)	(-3.15)	(-1.44)	(-4.00)	(-1.46)	(-2.76)	(-1.79)	(-2.08)	(-2.18)	(-2.47)	(-1.96)	(-4.01)	(-2.04)	(-1.79)
Covenant	-0.0274	0.0708**	-0.0679*	0.0869**	-0.0041	0.0166	-0.0018	0.0105	-0.0049	0.0209	0.0069	0.0446	-0.0243	0.0322
	(-0.68)	(2.39)	(-1.86)	(2.38)	(-0.13)	(0.49)	(-0.06)	(0.26)	(-0.16)	(0.55)	(0.21)	(1.02)	(-0.83)	(0.81)
Performance	0.1001**	0.0159	0.0367	0.0570	0.0065	0.0992***	0.0784**	0.0368	0.0072	0.0784**	0.0540*	0.0697	0.0052	0.1028***
	(2.58)	(0.49)	(1.16)	(1.57)	(0.23)	(2.97)	(2.38)	(1.23)	(0.21)	(2.37)	(1.87)	(1.56)	(0.19)	(2.86)
Collateral	0.2833***	0.0865	0.2255***	0.1997**	0.2009***	0.2918***	0.4297***	0.0678	0.2734***	0.2907***	0.2226***	0.3071**	0.2426***	0.3317***
	(4.34)	(0.99)	(3.24)	(2.16)	(2.73)	(3.74)	(4.99)	(1.12)	(4.18)	(3.14)	(3.14)	(2.37)	(4.72)	(3.53)
Lead Arrangers	0.0221***	0.0261***	0.0110	0.0273***	0.0021	0.0259***	0.0187***	0.0098	0.0162**	0.0144*	0.0185**	0.0157**	0.0169***	0.0134*
	(2.74)	(4.22)	(1.21)	(4.35)	(0.27)	(4.15)	(2.78)	(1.34)	(2.09)	(1.81)	(2.41)	(2.34)	(2.68)	(1.82)
Credit Spread	0.7652	0.5104	0.6346	0.4200	0.1127	0.6028	0.5555	0.9987**	0.1615	0.2599	0.7235	-0.1215	0.2694	1.0503**
	(1.30)	(0.83)	(1.10)	(0.68)	(0.19)	(1.23)	(0.86)	(2.03)	(0.26)	(0.49)	(1.38)	(-0.17)	(0.44)	(2.11)
Term Spread	-0.0126	-0.0962*	-0.0294	-0.0691	-0.0547	-0.0475	-0.0528	0.0019	-0.0100	-0.0985*	-0.0220	-0.1365*	-0.0561	-0.0228
	(-0.33)	(-1.85)	(-0.77)	(-1.23)	(-1.00)	(-1.42)	(-1.12)	(0.07)	(-0.29)	(-1.81)	(-0.62)	(-1.90)	(-1.25)	(-0.58)
Constant	4.1405***	4.1940***	4.3679***	4.5315***	4.9165***	4.5758***	4.5554***	3.6828***	4.5707***	4.0322***	4.1486***	5.3398***	4.3570***	3.9999***
	(6.20)	(6.39)	(6.78)	(6.69)	(7.96)	(8.32)	(6.06)	(6.95)	(6.76)	(6.77)	(7.14)	(6.18)	(6.85)	(6.52)
Observations	841	832	821	860	838	1,084	869	767	818	819	1,171	465	801	838
R-squared	0.599	0.499	0.494	0.601	0.548	0.575	0.557	0.545	0.548	0.553	0.530	0.620	0.478	0.580
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Loan type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the exploration of a governance channel in driving the relationship between firm waste and loan spreads. The specifications investigate the variables of *Independent*, *Busy*, *Board Size*, *Duality, Ln(Exec Comp)*, *Board Attendance*, and *Governance*. Loan and year fixed effects are included. Variable definitions are provided in Table A2. T-statistics are reported in parentheses and standard errors are clustered at the firm-level.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. For brevity, coefficients on fixed effects are not reported.

Table 8: Preference Channel Subsample Analysis

Variables	Political Leaning		ESG Score	
	Republican	Democratic	Low	High
	(1)	(2)	(3)	(4)
	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)
Panel A: Waste/Sales				
Waste/Sales	0.0069*	0.0033	0.0464*	-0.0004
	(1.99)	(0.29)	(1.95)	(-0.15)
Ln(Assets)	-0.0420	-0.0405***	-0.0654***	-0.0431**
	(-0.94)	(-3.07)	(-4.34)	(-2.01)
Leverage	0.7888***	0.0836	0.0997	0.2123
	(3.20)	(0.53)	(0.85)	(0.90)
MTB	-0.0014	-0.0010	-0.0019**	-0.0002
	(-0.72)	(-1.29)	(-2.22)	(-0.12)
Tangibility	0.1485	0.2502***	0.1254**	0.3617***
	(0.98)	(4.13)	(2.08)	(3.50)
Profitability	-0.1343	-1.5800***	-0.9421***	-1.7088***
	(-0.29)	(-4.41)	(-4.37)	(-2.64)
Shareprice_Vol	1.6055***	1.5482***	0.9822***	2.1776***
	(3.77)	(5.81)	(4.66)	(5.86)
Ln(Maturity)	0.1315	0.0331	0.0562	0.0008
	(1.65)	(1.01)	(1.61)	(0.01)
Ln(Size)	-0.0387	-0.0494***	-0.0259	-0.0524**
	(-1.21)	(-2.81)	(-1.59)	(-2.13)
Covenant	0.0422	0.0197	-0.0168	0.0696*
	(0.89)	(0.72)	(-0.60)	(1.88)
Performance	0.1670***	0.0227	0.0071	0.0743**
	(3.13)	(0.83)	(0.23)	(1.98)
Collateral	0.2370**	0.2100***	0.2408***	0.2391**
	(2.51)	(3.22)	(4.37)	(2.50)
Lead Arrangers	0.0225**	0.0167**	0.0259***	0.0148**
	(2.16)	(2.56)	(3.34)	(2.12)
Credit Spread	-1.3774*	0.7122	0.5850	0.5927
	(-1.73)	(1.44)	(1.07)	(1.01)
Term Spread	-0.0295	-0.0252	-0.0484	-0.0057
	(-0.68)	(-0.53)	(-1.29)	(-0.08)
Constant	5.7433***	4.3459***	4.5298***	4.4611***
	(6.96)	(7.68)	(7.49)	(6.13)
Observations	321	1,315	828	821
R-squared	0.590	0.561	0.594	0.557
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Loan type	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes

	(1)	(2)	(3)	(4)
	Ln(Spread)	Ln(Spread)	Ln(Spread)	Ln(Spread)
Panel B: Waste/Assets				
Waste/Assets	0.0253*	0.0118	0.0717	0.0001
	(1.94)	(0.63)	(1.57)	(0.01)
Ln(Assets)	-0.0410	-0.0400***	-0.0609***	-0.0429**
	(-0.92)	(-2.99)	(-4.07)	(-1.98)
Leverage	0.7899***	0.0820	0.1016	0.2123

	(3.21)	(0.52)	(0.87)	(0.90)
MTB	-0.0015	-0.0010	-0.0018**	-0.0002
	(-0.73)	(-1.29)	(-2.15)	(-0.12)
Tangibility	0.1479	0.2486***	0.1371**	0.3600***
	(0.97)	(4.12)	(2.35)	(3.48)
Profitability	-0.1364	-1.5798***	-0.9580***	-1.7068***
	(-0.29)	(-4.43)	(-4.45)	(-2.64)
Shareprice_Vol	1.5836***	1.5439***	0.9589***	2.1750***
	(3.75)	(5.77)	(4.54)	(5.83)
Ln(Maturity)	0.1308	0.0330	0.0590*	0.0009
	(1.65)	(1.01)	(1.66)	(0.02)
Ln(Size)	-0.0387	-0.0496***	-0.0288*	-0.0524**
	(-1.23)	(-2.82)	(-1.78)	(-2.13)
Covenant	0.0402	0.0199	-0.0151	0.0697*
	(0.84)	(0.73)	(-0.54)	(1.88)
Performance	0.1684***	0.0224	0.0068	0.0744**
	(3.15)	(0.82)	(0.22)	(1.98)
Collateral	0.2379**	0.2117***	0.2519***	0.2402**
	(2.52)	(3.23)	(4.61)	(2.50)
Lead Arrangers	0.0225**	0.0168**	0.0256***	0.0149**
	(2.17)	(2.56)	(3.32)	(2.13)
Credit Spread	-1.3548*	0.7093	0.5783	0.5977
	(-1.69)	(1.43)	(1.05)	(1.02)
Term Spread	-0.0296	-0.0252	-0.0452	-0.0057
	(-0.69)	(-0.53)	(-1.22)	(-0.08)
Constant	5.7139***	4.3478***	4.5087***	4.4533***
	(6.90)	(7.68)	(7.44)	(6.14)
Observations	321	1,315	828	821
R-squared	0.591	0.561	0.593	0.557
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Loan type	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes

This table presents the exploration of a preference channel in driving the relationship between firm waste and loan spreads. Models (1)–(2) explore the role of firms' political leanings, proxied by *Politic*, which is a dummy variable equal to one if the firm is headquartered in a Republican state, and zero otherwise. Models (3)-(4) explore the role of firms' ESG scores. Loan and year fixed effects are included. Variable definitions are provided in Table A2. T-statistics are reported in parentheses and standard errors are clustered at the firm-level.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. For brevity, coefficients on fixed effects are not reported.

Table 9: Two-Stage Least Squares Test

Variables	1st Stage (1) Waste/Sales	2nd Stage (2) Ln(Spread)	1st Stage (3) Waste/Sales	2nd Stage (4) Ln(Spread)	1st Stage (5) Waste/Sales	2nd Stage (6) Ln(Spread)
Panel A: Waste/Sales						
IA_Waste/Sales	0.1075**				0.0655	
	(1.97)				(1.48)	
L2.Waste/Sales			0.1171***		0.1122***	
			(15.46)		(14.89)	
Waste/Sales		0.1892*		0.0508*		0.0589*
		(1.67)		(1.94)		(1.87)
Constant	4.2157**	4.5252***	3.8733*	5.8734***	3.4231	5.6703***
	(2.44)	(4.94)	(1.79)	(6.25)	(1.62)	(5.94)
Control for						
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,628	1,628	1,333	1,333	1,326	1,326
R-squared	0.985	0.785	0.951	0.801	0.953	0.802
F-stat	3.86		238.93		147.86	
Cragg-Donald	83.26		816.47		442.85	
	(1) Waste/Assets	(2) Ln(Spread)	(3) Waste/Assets	(4) Ln(Spread)	(5) Waste/Assets	(6) Ln(Spread)
Panel B: Waste/Assets						
IA_Waste/Assets	0.1716**				0.1698**	
	(2.34)				(2.00)	
L2.Waste/Assets			0.1403***		0.1277***	
			(12.95)		(22.10)	
Waste/Assets		0.3856**		0.1179**		0.1539**
		(2.29)		(2.17)		(2.21)
Constant	1.5869***	4.6468***	1.8180**	5.8569***	1.3084*	5.6161***
	(2.64)	(5.63)	(2.01)	(6.26)	(1.95)	(5.89)
Control for						
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,628	1,628	1,333	1,333	1,326	1,326
R-squared	0.974	0.787	0.950	0.802	0.959	0.803
F-stat	5.47		167.80		374.96	
Cragg-Donald	175.05		858.51		629.32	

This table presents the 2SLS approach exploring the effects of firm waste practices on loan costs using industry-year average waste and lagged waste as instruments. Panel A presents the analysis of *Waste/Sales*, while Panel B presents *Waste/Assets*. Columns (1)-(2) present the first and second stage regressions using industry average waste (IA_Waste) as an instrument. Columns (3)-(4) present the first and second stage regressions using lagged waste (L2.Waste) as an instrument. Columns (5)-(6) present the first and second stage regressions using both instruments simultaneously. Firm, loan and year fixed effects are included. Variable definitions are provided in Table A2. T-statistics are reported in parentheses and standard errors are clustered at the firm-level.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. For brevity, coefficients on control variables and fixed effects are not reported.

Table 10: Propensity Score Matching Test

Variables	Pre-match (1) Treatment (High Waste/Sales)	Post-match (2) Treatment (High Waste/Sales)
Panel A: Logit Regression Predicted Estimates		
Ln(Assets)	-0.3912***	0.0022
	(-9.17)	(0.01)
Leverage	1.0337***	-0.5753
	(2.93)	(-0.48)
MTB	0.0021	-0.0077
	(0.58)	(-0.92)
Tangibility	2.0151***	0.2342
	(9.11)	(0.23)
Profitability	0.1284	0.5615
	(0.17)	(0.28)
Shareprice_vol	-2.3702***	0.9149
	(-3.75)	(0.36)
Constant	3.4072***	-0.1785
	(6.93)	(-0.10)
Observations	1,630	442
Year FE	No	No
Firm FE	No	No
Loan type	No	No
Loan purpose	No	No

Variables	Treated	Controls	Difference	T-stat
Panel B: Mean Firm Differences				
Ln(Assets)	9.8465	9.8486	-0.0021	-0.02
Leverage	0.3460	0.3586	-0.0126	-0.83
MTB	2.0289	3.7008	-1.6719	-1.19
Tangibility	0.3885	0.3710	0.0175	0.75
Profitability	0.1275	0.1241	0.0033	0.42
Shareprice_vol	0.2471	0.2384	0.0086	1.04

Variables	Treated	Controls	Difference	T-stat
Panel C: Propensity Score Matching Estimator				
Ln(Spread)	4.9528	4.8674	0.0854*	1.82

This table presents the propensity score matching estimation. The variable *Treatment* is equal to one if a firm's waste intensity is above the sample median, and zero if below. Panel A reports the propensity score estimates from the logit model, and the first diagnostic test of the post-match sample. Panel B presents the mean firm differences. Panel C presents the average treatment effect on *Ln(Spread)* for the matched sample. Variable definitions are provided in Table A2. T-statistics are reported in parentheses in Panel A.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 11: Effects of Waste Management Practices on Total Cost of Borrowing and Fees

Variables	(1) Ln(TCB)	(2) Ln(TCB)	(3) Ln(TCB)	(4) Ln(Fees)	(5) Ln(Fees)	(6) Ln(Fees)
Waste/Sales	0.0943***			0.1033**		
	(3.95)			(2.24)		
Waste/Assets		0.2305***			0.3269***	
		(3.87)			(2.65)	
Rec_Ratio			-0.0307			-0.3258*
			(-0.30)			(-1.96)
Constant	4.9408***	4.9153***	5.7214***	2.8565	2.9031	1.9995
	(4.95)	(4.87)	(4.76)	(1.02)	(1.04)	(0.68)
Control for						
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,636	1,636	1,379	800	800	694
R-squared	0.802	0.803	0.813	0.904	0.905	0.911

This table presents the effects of firm waste practices on alternative measures of loan costs. Columns (1)–(3) explore the effects on *Ln(TCB)*, while columns (4)–(6) explore the effects on *Ln(Fees)*. Firm, loan and year fixed effects are included. Variable definitions are provided in Table A2. T-statistics are reported in parentheses and standard errors are clustered at the firm-level.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. For brevity, coefficients on control variables and fixed effects are not reported.

Table 12: Effects of Waste Management Practices on Nonprice Loan Terms

Variables	(1) Ln(Maturity)	(2) Ln(Size)	(3) Lead Arrangers	(4) Covenant
Panel A: Waste/Sales				
Waste/Sales	0.0353	-0.1487*	0.3285	-0.1477
	(1.01)	(-1.85)	(0.85)	(-0.57)
Constant	1.9929	2.5852	10.0760	14.4582**
	(1.31)	(0.98)	(1.06)	(2.06)
Control for				
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes
Observations	1,636	1,636	1,636	977
R-squared	0.771	0.675	0.791	
Pseudo R-squared				0.366
	(1) Ln(Maturity)	(2) Ln(Size)	(3) Lead Arrangers	(4) Covenant
Panel B: Waste/Assets				
Waste/Assets	-0.0218	-0.2368	0.5395	0.1442
	(-0.31)	(-1.18)	(0.64)	(0.32)
Constant	2.1893	2.3710	10.5641	13.3923*
	(1.45)	(0.90)	(1.11)	(1.94)
Control for				
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes
Observations	1,636	1,636	1,636	977
R-squared	0.771	0.674	0.790	
Pseudo R-squared				0.365
	(1) Ln(Maturity)	(2) Ln(Size)	(3) Lead Arrangers	(4) Covenant
Panel C: Rec_Ratio				
Rec_Ratio	0.0268	0.0225	-0.1657	1.2562**
	(0.21)	(0.11)	(-0.18)	(2.07)
Constant	2.3315	3.2830	13.0786	7.0007
	(1.32)	(1.08)	(1.37)	(1.10)
Control for				
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes
Observations	1,379	1,379	1,379	829
R-squared	0.775	0.697	0.769	
Pseudo R-squared				0.404

This table presents the effects of firm waste practices on nonprice loan features. Panels A, B and C reflect investigations into *Waste/Sales*, *Waste/Assets*, and *Rec_Ratio*, respectively. Column (1) explores the effect on *Ln(Maturity)*. Column (2) explores the effect on *Ln(Size)*. Column (3) explores the effect on *Lead_Arrangers*. Column (4) explores the probit regression on *Covenant*. Firm, loan and year fixed effects are included. Variable definitions are provided in Table A2. T-statistics are reported in parentheses and standard errors are clustered at the firm-level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. For brevity, coefficients on control variables and fixed effects are not reported.