Credit risk differentials between green and non-green SMEs[1]

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Abstract

Small and Medium-sized Enterprises (SMEs) form the backbone of the economy both in terms of value added and employment, making them essential to reach economy-wide decarbonization goals. To invest in decarbonization, SMEs mainly rely on bank lending as an external source of capital. When providing such lending, a bank needs to assess the creditworthiness of the SME, yet public knowledge on this assessment is scarce because bank lending data is proprietary and SMEs are mostly exempt from reporting requirements. In this article, we construct a 10-year panel dataset covering the loan portfolios of 11 banks from the SME-specialized banking group ProCredit to analyze the difference in default probabilities between green and non-green SMEs. The dataset covers lending to >43,000 SMEs, of which 20.5% use a green loan at some point, by banks in Albania, Bosnia and Herzegovina, Bulgaria, Ecuador, Georgia, Kosovo, Northern Macedonia, Moldova, Romania, Serbia, and Ukraine. We employ a two-way fixed effects regression model with matching at the firm level and find a reduction of ~16% in the probability of default for green SMEs, controlling for credit risk and other credit-relevant firm characteristics. Using data on the use of proceeds of these loans, we find the largest risk reduction effect for solar PV installations (~40%), followed by energy efficiency investments (~13%), with no significant effects for other green investments, indicating a potential hedging effect against energy price fluctuations. We further find that this effect is slightly positively related to the intensity of green lending and inversely related to the bank's risk rating, indicating an increased risk mitigation effect of green lending for SMEs with greater shares of green loans and those in financial distress. Our findings suggest that incorporating the observed risk differential into banks' risk and pricing models could improve financial market efficiency while simultaneously improving the availability of green loans to SMEs.

Keywords: Green loans, credit risk, ESG risk, SMEs

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1. Introduction

Small and medium-sized enterprises (SMEs) are central actors for the transition toward a low-carbon and climate-resilient economy. In the European Union (EU), SMEs, defined as companies with less than 250 employees, represent more than 99% of all companies and generate >60% of total employment and >50% of total value added (European Commission, 2025). Simultaneously, they account for around 40% of corporate emissions and 60–70% of industrial pollution, particularly in the manufacturing sector (Koirala, 2019; OECD, 2023). As such, greening SMEs is essential for achieving decarbonization targets, yet SMEs often lack the financial capacity to make decarbonization investments. Since banks are their primary source of external financing, green bank lending has become a key mechanism for enabling SMEs to invest in sustainable technologies and participate in the green transition.

Green debt financing can be addressed from either a pricing or a credit risk perspective. Most studies focus on publicly listed companies and the pricing of green financial instruments, for instance, identifying a green premium or 'greenium' for green bonds (Flammer, 2021; MacAskill et al., 2021). Credit risk is analyzed more seldomly and often at the macro level using indicators like bank-level non-performing loan (NPL) ratios, which are too aggregated for analyses of risk dynamics of small portfolio segments such as green loans (Zhou et al., 2022). Micro-level analyses using loan- or firm-level data are rare and have largely been restricted to specific national contexts, such as the Dutch mortgage market (Billio et al., 2022) or green finance in Romania (Neagu et al., 2024). Furthermore, many studies adopt broad or inconsistent definitions of green lending, making it difficult to interpret or compare results across different settings (Neagu et al., 2024). In this study, we contribute to the nascent literature on the risk dynamics of green finance by conducting an empirical analysis with a focus on the SME segment. We test whether there exists a default risk differential between SMEs that receive green finance compared to their non-green peers and attempt to estimate the magnitude of the differential across heterogeneous green uses of proceeds.

We analyze the relationship between green lending and credit risk using a novel firm-level panel dataset from the ProCredit Group, a development-oriented banking group mostly active in Southeastern and Eastern Europe (ProCredit Holding, 2025) and a leader in green SME finance (Spence, 2023). Based on a data sharing agreement with the ProCredit Group, we use a confidential panel dataset with data on SMEs and loan issuance from 2015 to 2024, covering >43.000 firms

out of which >8,800 (20.5%) received at least one green loan. Using the European Banking Authority's (EBA) definition of default, we find a significantly reduced default probability (~16%) for green SMEs compared to their non-green peers. The effect is found to be positively related to the share of green loans to total SME exposure, as an increase in the green share by 25 percentage points is associated with a reduction of the default probability of >5%. We further find this effect to be inversely related to the bank's risk rating, indicating an increased risk mitigation effect of green lending in situations of financial distress. We additionally estimate heterogeneous effects for different green uses of proceeds and find the largest risk reduction effect for solar PV installations (~40%), followed by energy efficiency investments (~13%), with no significant effects for other green investments.

This paper makes several contributions. First, we publish completely new data on green SME lending and provide the first multi-country empirical evidence on a credit risk differential between green and non-green SMEs using micro-level data. Second, we quantify this risk differential using a two-way fixed effects regression model with matching at the firm level. Third, we leverage ProCredit Group's internal data on the use of proceeds to identify heterogeneous effects on credit risk, depending on the type of investment for which the loan was used.

The remainder of the paper is structured as follows: Section 2 reviews the literature on credit risk in (green) SME lending. Section 3 presents the panel dataset, the main variables as well as the green loan classification system used by ProCredit Group and provides first insights into structural differences between green and non-green firms. Section 4 introduces the empirical methodology and Section 5 presents descriptive and regression results. Section 6 discusses the results, followed by a conclusion in Section 7.

2. Literature Review

A growing body of literature examines whether green debt instruments are priced differently from their conventional counterparts, and this green price premium has become known as the 'greenium'. Empirical studies on green bonds consistently document a yield discount relative to otherwise similar conventional bonds, suggesting that investors may accept lower returns in exchange for environmental alignment or ESG compliance (Baker et al., 2022; Karpf and Mandel, 2018; Zerbib, 2019). While the estimated greenium is typically small, often in the range of 1 to 10

basis points, it is statistically significant and persistent across primary and secondary markets. The yield differential is frequently attributed to investor preferences, regulatory incentives, or reputational benefits (Flammer, 2021; MacAskill et al., 2021). Recent research also extends these findings to sustainability-linked loans, where pricing advantages are observed in the form of reduced interest rates tied to ESG performance metrics (Pohl et al., 2023).

A fundamental principle in finance and a regulatory requirement in banking is that pricing should be based on underlying risks (EBA, 2020). Policymakers and regulators, particularly in the EU, increasingly require banks to consider ESG in their financing decisions.[6] Recent research has demonstrated that ESG awareness and performance have a significant impact on credit risk performance (Brogi et al., 2022; Carnevale and Drago, 2024a). Unfortunately, this research analyzes only loans to large corporates with an ESG rating and cannot be applied to SMEs, where ESG scores are typically not available (Carnevale and Drago, 2024b). The literature on green credit-risk differentials forms a distinct and important subset of the broader research on ESG-related financial risks. Research on credit risk differentials in green bank lending can be categorized into three segments: bank-level analyses, loan-level analyses of green mortgages, and a single loan-level study on green SMEs in Romania.

Research based on bank-level data finds correlations between a higher share of green lending and a lower level of non-performing loan (NPL) ratios. Studies conducted based on Chinese banks affected by the China Green Credit Policy suggest that government-led green credit policies enhance the financial performance of banks (Cui et al., 2018). However, smaller local banks may face increased credit risk due to their limited capacity to manage green loans. The identified effects vary based on bank ownership and institutional resources, reflecting the broader influence of government-led green credit policies on banks' financial performance and sustainability integration (Weber, 2017; Yin et al., 2021; Zhou et al., 2022). Similar results of green lending being associated with lower NPL ratios have been found by Mirza et al. (2023) for BRICs (Brazil, Russia, India, China) and by Al-Qudah et al. (2022) for the United Arab Emirates. The same result has been found by Umar et al. (2021) in the only study covering the Eurozone banking sector. In the absence of a standardized definition, the authors use the terms "carbon-neutral," "low-carbon,"

[6] Directive 2013/36/EU Article 87a(5) mandates EBA to issue its Guidelines on the management of environmental, social and governance (ESG) risks (EBA/GL/2025/01).

and "green lending" interchangeably. They demonstrate that carbon-neutral lending improves bank-level credit risk indicators, attributing their findings to a reduced cash-flow volatility of these borrowers. In summary, these studies, which employ panel regression techniques including fixed and random effects models, indicate that green lending is associated with improved credit risk performance at the bank level. A key limitation of these studies remains the usage of the highly aggregated bank-level NPL ratio rather than loan or firm-level data to measure default risk. the studies using bank-level data apply

On a micro level, research on the performance of green versus non-green loans mainly analyzes mortgage loan data. Billio et al. (2022) use loan-level data from the Dutch mortgage market and find that energy efficiency in buildings is inversely associated with mortgage default risk, primarily because efficient buildings lead to lower utility bills, increasing borrowers' disposable income and decreasing the likelihood of default. An and Pivo (2020) reach a similar conclusion based on loan-level data from the US mortgage market and estimate a 34% reduction in the relative default risk of commercial mortgage-backed loans compared to the average if the building is energy efficient. Compared to the less standardized and more heterogeneous SME lending segment, these studies benefit from standardized data and homogeneous use of proceeds in the mortgage lending segment and apply survival analysis, matching and fixed effects logit regressions.

The only paper known to us that analyzes micro-level SME loan data reaches a different conclusion than previously discussed papers. Neagu et al. (2024) work with confidential loan-level data from the Romanian central bank, use a penalized multivariate and a fixed effects logit model, and apply propensity score matching of green and non-green loans. The study finds no significant evidence that green loans granted by Romanian financial institutions from 2010 to 2020 are associated with lower credit risk compared to conventional loans. However, the authors acknowledge that a key limitation of their study is the use of data from a period when the Romanian government retroactively changed its renewable energy support policies, leading to damaging effects on firms that had invested in renewables. Renewable energy loans are the most relevant category in their sample, and their default rate rose from 0% to 20% after the retroactive policy changes. This, together with the small sample size of fewer than 4,000 green loans, may explain why the authors found a null effect of green loans on credit risk, in contrast to previous studies. Our paper

complements this nascent literature on credit risk differentials between green and non-green and by focusing on SMEs using a large cross-country panel dataset.

The multitude of methods applied in these studies reflects fundamental differences in data availability and research foci. In the area of mortgage finance, credit risk is typically assessed at the loan level because banks follow a product-based approach, and default events are generally disconnected from one another. In the area of SME banking, credit risk is typically assessed at the firm level via an annual risk rating because banks tend to follow a house-bank approach (as is the case for ProCredit Group), and according to the EBA definition of default, a default on any loan triggers the contagion principle, leading to a risk spillover at the firm level. We therefore decided to set up our panel dataset at the firm level, aggregating all loans of one firm into a single firm-year observation. Our database includes annual risk ratings and default events at the firm level, as well as additional details on the use of proceeds from green loans. As we aim to investigate whether green SMEs default differently from non-green SMEs and to estimate the magnitude of this effect, we design our study differently from Neagu et al. (2024) as a univariate model with the default as the dependent variable and risk rating and green as the main covariates. The risk ratings allow us to explicitly control for credit risk at the SME level, and we utilize the green loan classifications to identify heterogeneous effects across different uses of proceeds. In line with Neagu et al. (2024) we choose a fixed effects (FE) model and use matching, but we opt for a linear probability FE model over a logit FE model. Because the default probabilities in our sample are small, the FE linear probability model provides a very good approximation to a nonlinear response, while allowing us to utilize the full panel. This research design allows us to assess whether SMEs that receive green loans have a different default probability than their non-green counterparts.

3. Data

3.1 Green loan classification

The main reason for the lack of research on green SME finance is the limited availability of data. While recent EU regulatory developments are expected to improve data availability, the SME segment remains largely exempt from reporting requirements. As of 2024, banks in the EU are required to report their Green Asset Ratio (GAR) based on the EU Taxonomy for Sustainable

Activities.[7] However, there is no reporting on green SME lending because the EU Taxonomy and the Corporate Sustainability Reporting Directive (CSRD) have been designed for larger firms with more than 250 employees and a turnover above EUR 50 million (*Directive (EU) 2022/2464*, 2022), and the GAR includes only lending to this segment.[8] While some larger or sustainability-focused banking groups voluntarily or as part of their green bond reporting provide more details on their green assets, they are typically reported for green buildings and renewable energy and not for green SME lending.[9]

ProCredit is an example of such a sustainability-focused banking group and introduced its first green loan product in 2006, initially as part of green finance programs subsidized by International Financial Institutions (IFIs). These programs required detailed reporting on the use of proceeds, which led to the creation of internal monitoring and reporting structures. Due to continued investment demand from SMEs independent of subsidy programs, until 2015, ProCredit institutionalized green finance throughout its entire operations and developed its own internal green loan classification system based on international best practice, with the support of external consultants and regular second-party verification (Sustainalytics, 2024).

While the bank's methodology for the green classification system has been updated regularly to reflect evolving technologies and standards, the core structure has remained stable and consists of three main categories: Loans for energy efficiency, renewable energy, and green measures. These three categories of green lending are broken down with technical eligibility criteria for each subcategory (see Table A1 in the Appendix for the complete list of subcategories). To assign loans to their respective categories, ProCredit Group tracks the use of loan proceeds during disbursement and utilizes an automated IT system to classify each loan as either green or non-green, assigning green loans to a specific subcategory. For larger non-standard cases, this process is conducted

[7] According to articles 10 and 12 of the Commission Delegated Regulation (EU) 2021/2178 and the European Parliament and Council Regulation (EU) 2020/852.
[8] The numerator only includes assets related to large firms, while the denominator is not restricted in this way. The voluntary Banking Book Taxonomy Alignment Ratio (BTAR), introduced in 2024 by EBA in its Pillar 3 disclosures on ESG risks, addresses this issue by allowing financial institutions to voluntarily include green loans to SMEs in the numerator.
[9] See for example the sustainability reports of Société Générale and Santander. Apart from ProCredit, only the Latvian Group, AS LHV Group, voluntarily reported the renewable energy loan share in their SME portfolio once in their 2021 annual report.

manually and can involve an energy audit. Loans can also be partially green and/or assigned to different subcategories, depending on the share of the proceeds used for different activities.

3.2 Firm-level dataset and variable construction

We construct our firm-level panel dataset by merging data from several ProCredit Group internal databases, which contain data from ProCredit subsidiary banks in Albania, Bosnia and Herzegovina, Bulgaria (including operations in Greece), Ecuador, Georgia, Kosovo, Northern Macedonia, Moldova, Romania, Serbia, and Ukraine from 2015 to 2024. Specifically, we extracted firm-level end-of-year data on green and non-green SME lending, SME credit ratings, and default events. Our main dependent variable to measure credit risk reflects recorded default events at the firm level. Consistent with a firm-level credit risk approach, as defined by the EBA[10], we treat the first occurrence of default of any loan as a default event affecting all loans of the firm. To ensure that loans, which are written off or repaid in the same year as they default, are captured, the variable is defined as defaulted in the observed year and/or the following year. Our main variable of interest is *Green SME*, which we define as an SME with at least one outstanding green or partially green loan in the respective year. Each SME can have several outstanding loans, and a loan can be assigned to more than one of the three green use of proceeds categories (energy efficiency, renewable energy, and green measures). Our main control is the SME risk rating on an ordinal scale from 1 (low risk) to 7 (close to default). It aggregates qualitative and quantitative firm-level characteristics, including key financial data (current ratio, return on average assets, debt to EBITDA) and a firm-level assessment of qualitative factors, such as management quality and market position. For robustness checks, we also use the underlying financial data directly as controls instead of the SME risk ratings. Where multiple risk rating entries exist for the same year, the simple average is used.

3.3 Summary Statistics

Table 1 shows firm-level covariates for green and non-green SMEs. The 10-year panel dataset comprises 43,069 SMEs, of which 34,248 (79.5%) are non-green and 8,821 (20.5%) are green, resulting in a sample size of 172,620 firm-year observations. Note that due to data quality issues in the first years of the panel, the underlying financials are only available for at least 75% of the sample, whereas the risk rating is available for all SMEs. Green SMEs have around three times

[10] EBA defines default events as either: 90 days past due, unlikeliness to pay, or firm/group-level contagion (contamination principle). See EBA/GL/2016/07.

larger outstanding loan exposures than non-green SMEs (482 vs. 164 tEUR), and these are more frequently used for investment purposes rather than working capital (69% vs. 45%). Consequently, they show much longer maximum loan maturities (74 vs. 59 months) and appear slightly longer in the panel (6.9 vs. 6.4 years) despite having a slightly shorter history with the bank (5.7 vs. 6 years). Green SMEs exhibit significantly lower default rates (3.19% vs. 6.07%) despite an almost identical risk rating (both 3.4) and underlying financials. Additionally, SMEs that take out green loans are concentrated in key economic sectors, reflecting sector-specific differences in green investment potential. The highest shares of green SMEs are found in the electricity sector, and the highest number of loans is in agriculture and manufacturing. In contrast, wholesale and retail trade show a comparatively lower share of green SMEs (see Table A2 in the Appendix). Based on these observed structural differences between green and non-green SMEs, we control for unbalanced distribution and a potential selection bias in our further analysis.

Table 1: *Summary Table for Non-Green and Green SME observations*

	Non-Green SME Observations				Green SME Observations			
Variables	No. Obs.	Mean	Median	St. Dev.	No. Obs.	Mean	Median	St. Dev.
Default	142,423	0.0607	0	0.24	30,197	0.0319	0	0.18
Risk Rating	142,423	3.4017	3	1.12	30,197	3.4193	3	1.05
Total Loan Exposure [EUR]	142,423	163,743	64,764	352,289	30,197	481,770	196,571	820,776
Firm Tenure [years]	142,423	6.0440	5	4.74	30,197	5.7324	5	4.60
Years in Panel	142,423	6.3656	7	2.82	30,197	6.8904	7	2.63
Max Maturity [months]	142,394	58.9388	53	41.89	30,197	73.9484	60.5	34.88
Fixed Assets	142,423	0.4535	0	0.50	30,197	0.6873	1	0.46
Working Capital	142,423	0.4582	0	0.50	30,197	0.2442	0	0.43
Financials								
RoAA	104,594	5.8811	6	1.37	25,663	5.6835	6	1.39
Debt/EBITDA	104,747	4.0858	4	1.86	25,692	4.2648	4	1.76
Current Ratio	139,571	2.5793	2	1.36	29,868	2.5337	2	1.37

Notes: Firm Tenure=Number of years since the SME started banking with ProCredit Group (includes values outside of the panel and non-loan activities, defined to increase by 1 per year), Years in Panel=Number of years a firm appears in the panel (defined as constant value), Max Maturity=Longest maturity of any outstanding loan contract measured in months, Fixed Assets=Binary dummy marking if the majority of the total loan exposure finances fixed assets, Working Capital= Binary dummy marking if the majority of the total loan exposure finances working capital, RoAA=Return on average assets, Debt/EBITDA=Total debt capital divided by earnings before interest, taxes, depreciation, and amortization.

4. Methodology

4.1 Empirical Specification

The empirical approach of this paper examines whether, after controlling for various firm characteristics that explain credit default risk, a risk differential remains for green and non-green SMEs. Conceptually, credit default is a function of financial factors, such as liquidity, profitability, and financial leverage, as well as qualitative firm characteristics, such as market position and managerial quality, all of which are reflected in the credit risk rating assigned to the firm by the lending bank. Additional factors that may further explain default risk include the size of the firm, macroeconomic conditions, the quality of the firm-bank relationship, and the year and country in which the loan is originated (Ciampi et al., 2021).

As discussed in Section 2, micro-level studies similar to ours apply survival analysis, fixed effects logit models and matching. Due to the EBA defining default at the firm level, we decided to structure our dataset at the firm level and include firm-fixed effects to analyze within-firm variation. The vast majority of firms never default over the observation window, while the remaining firms experience at most a single transition from non-default to default. In such a setting, a conditional fixed-effects logit model would rely for identification only on the small subset of firms that both default and exhibit within-firm changes in green status (<1% of firms), dropping all firms with no variation in both variables. To fully exploit the panel while controlling for time-invariant firm heterogeneity, we employ a linear probability model with firm fixed effects and standard errors clustered at the firm level. With default probabilities around 5%, the linear probability specification closely approximates a nonlinear response while delivering directly interpretable marginal effects in percentage points.

As explained in Section 3, for our primary mode of estimation, we compile a panel dataset that captures the evolution of firms through time. With observation of the same set of firms over multiple years as they obtain different types of loans, we propose estimating a regression specification as follows to measure the effect of green loans on SME default risk:

$$Default_{i,t} = \beta_0 + \beta_1 Green_{i,t} + \beta_2 X_{i,t} + \alpha_t + \mu_i + \varepsilon_{i,t} \quad (1)$$

where $Default_{i,t}$ refers to the loan default status of firm i in year t. It takes a dummy value 1 if the firm is in default in that given year or the next and 0 otherwise; *Green* refers to the green classification of the firm's loan contracts measured either (i) as a dummy variable indicating 1 if any loan by that firm i is classified green in that year, or (ii) as a discrete variable defined as the green share of the firm's total loan exposure. Both these variables are time-varying as the firm's status changes when it signs new loan contracts, which can be with or without a green component. As an additional specification, we use green lending categories to identify heterogeneous effects across the different uses of proceeds: energy efficiency, renewable energy, and green measures.

$X_{i,t}$ is a matrix of firm-level characteristics for firm i including the log of the firm's total loan exposure, maximum loan maturity, firm tenure, dummy variables indicating the firm's main loan purpose (fixed assets or working capital), and variables related to the assigned risk rating and its underlying financial ratios (debt/EDITDA, RoAA, current ratio). α_t refers to the year fixed effects, which control for time-specific factors that might affect all firms in the same way across different years. μ_i refers to firm fixed effects, which control for unobserved heterogeneity specific to each firm and that does not change over time (such as management quality or unobserved firm characteristics). Finally, $\varepsilon_{i,t}$ is the error term which captures the random shock to the firm's outcome at time t with standard errors clustered at the firm level to account for potential correlation of errors within firms over time.

The main coefficient of interest β_1 measures the marginal effect of the green status on the probability of default. The variables in the matrix $X_{i,t}$ control for factors that may drive the probability of default, but which may also be correlated with whether a firm is classified as green. The bank's internal risk rating, produced through rigorous analysis and annual validations, serves as a key predictor of default and is hence expected to show a strong positive correlation. Additional control variables are selected based on data availability and best practices in the literature (Ciampi et al., 2021). Macroeconomic indicators are omitted due to country fixed effects. We expect the size of the loan to be negatively correlated with the probability of default as such loans are on the one hand connected with a more thorough analysis and monitoring on the side of the bank while on the other hand, they can be a useful proxy for the size of the firm, which is not captured by any other variable in our dataset (EBA, 2024). Firm tenure reflects the importance of relationship banking in the SME segment, which is expected to be associated with a negative correlation.

However, as new bank clients are most thoroughly screened before the first lending activity, they tend not to default in the first years hence the relationship could also be non-linear. We expect a positive correlation with maturity due to increased uncertainty.

4.2 Estimation strategies and matching

We use a Linear Probability Model (LPM) with a binary dependent variable, fixed effects, and matching to measure the differential default risk of SMEs that receive green loans.

In the first specification, we examine SMEs that have any active, outstanding green loans. In the second specification, we replace the binary green indicator with the continuous green share of total SME exposure to identify potential intensity effects of green lending. In the third specification, we replace Green SME with its three subcategories to gain further insights into the types of investments that drive the aggregated green dynamics. In the fourth, fifth and sixth specifications, we repeat the same regressions as in the first three specifications based on the matched sample to address potential biases in the dataset stemming from the structural differences between green and non-green SMEs discussed in Section 3.3.

Finally, we relax the assumption of a homogeneous association between green status and default risk that is implicit in prior studies focusing on realized default events (An and Pivo, 2020; Billio et al., 2022; Neagu et al., 2024). We do so by interacting the green status with the firm's internal risk rating, allowing the marginal association between green status and default probability to vary across different levels of ex-ante financial risk. We test for heterogeneous treatment effects in the green–default relationship along the SME risk spectrum, while preserving the firm fixed-effects structure and matching approach employed in the baseline models.

4.2.1 Fixed effects

This study goes beyond previous studies (Neagu et al., 2024), by adding firm fixed effects to control for time-invariant characteristics at the firm level, including those that are unobservable. Our dataset primarily focuses on family-owned SMEs with relatively stable characteristics in terms of ownership, management quality, and market position. This makes fixed effects a robust control that helps isolate the marginal impact of changing green loan status on default risk while mitigating bias from unmeasured, stable firm characteristics. Controlling additionally for year fixed effects is crucial because these fixed effects collectively capture unobserved heterogeneity and external factors that affect default risk such as common macroeconomic shocks. Note that country and

sector fixed effects are omitted due to perfect multicollinearity with firm fixed effects; however, they are incorporated in the matching approach to address the remaining heterogeneity.

4.2.2 Two-step matching

To ensure that we compare green SMEs with observationally similar non-green SMEs, we apply a matching methodology. This also helps mitigate the effects of unbalanced distribution and selection bias discussed in Section 3.3. We apply a two-step matching process to combine the benefits of two matching methodologies and compensate for some of the shortcomings of Propensity Score Matching (King and Nielsen, 2019).

Coarsened Exact Matching (CEM) is first applied to the dataset to create strata in which treated and control units are exactly matched on country, sector, and a binned measure of years in panel. Firms are grouped into three categories based on the number of years they appear in the panel: 1-3 years, 4–7 years, and 7-10 years. Only strata containing both treated and control units are retained, which restricts the analysis to the region of common support and improves balance on these dimensions. Within the CEM-matched sample, as a second step, Propensity Score Matching is conducted to further balance the distribution of relevant continuous covariates. Propensity scores are estimated using a logistic regression of treatment status (green) on the following averaged covariates: firm tenure, max. loan maturity, loan size, risk rating, and loan purpose indicators (fixed assets and working capital). One-to-one nearest neighbor matching is performed based on the estimated propensity scores, and only matched units with positive weights are retained for further analysis.

The effectiveness of the second-step matching procedure is assessed by comparing the distribution of covariates between the treated and control groups before and after matching. Table 2 shows that the mean difference between the control and treatment groups was reduced for all matching covariates and is no longer statistically significant after matching. In addition, the variance ratios between treated and control groups move closer to unity after matching, indicating improved balance not only in means but also in the dispersion of covariates.

Table 2: *Covariate Balance Before and After Matching*

Variable	Matched (M) or unmatched (U) sample	Treated Mean	Control Mean	% Bias	% Bias Reduction	t	p>|t|	V(T)/V(C)
Risk Rating	U	3.37	3.33	4.1		2.71	0.007	0.80*
	M	3.37	3.36	1	75.7	0.52	0.6	0.84*
Loan Lize (ln)	U	11.61	10.52	55.8		34.31	0	0.51*
	M	11.61	11.59	1.3	97.7	0.81	0.416	1.11*
Firm Tenure	U	4.29	5.00	-16		-10.64	0	0.85*
	M	4.29	4.25	0.9	94.4	0.49	0.626	1.00
Max Maturity	U	65.08	54.97	28.5		18.58	0	0.75*
	M	65.08	64.67	1.2	95.9	0.62	0.536	0.84*
Fixed Assets	U	0.67	0.44	54.3		35.6	0	0.78*
	M	0.67	0.68	-2.7	95.1	-1.45	0.147	0.92*
Working Capital	U	0.26	0.46	-50.5		-32.08	0	0.64*
	M	0.26	0.26	0.5	98.9	0.3	0.761	0.89*

Notes: * if variance ratio outside [0.95; 1.05]

5. Results

5.1 Descriptive Results

Our 10-year panel comprises of >43.000 SMEs out of which 20.5% use a green loan at some point in time. Figure 1 illustrates the lending volumes of these SMEs, showing that their annual loan exposures amount up to EUR 5.6bn out of which significant shares are marked with a green purpose. After a strong growth in the first three years, approximately 40% of the total loan exposure is to green SMEs, i.e., SMEs that have at least one green loan outstanding at the end of the respective year. When analyzing only those loans with a green purpose, it appears that after an initial growth phase, market saturation is reached at around 17% of green loans, as measured on an aggregated portfolio level. The share of green lending varies significantly across sectors (see Table A2 in the Appendix). Notably, the the smaller sectors, energy (~70%) and waste management (~55%), have substantially higher green lending shares compared to the largest sector in our sample, wholesale and retail trade (<10%). Other significant sectors include agriculture (15%), which demonstrates considerable green lending potential, and manufacturing (23%), which shows significant green lending opportunities. These sector-specific values offer important insights into the green investment and lending potential within the SME segment, contributing to more accurate future estimates of the investment gap in its green transition.

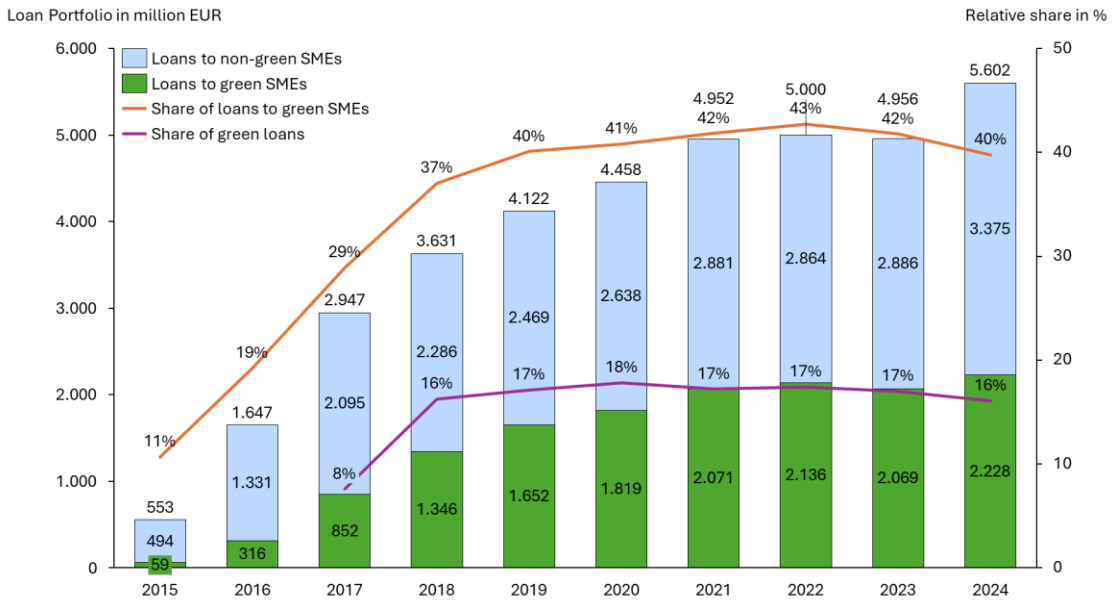


Figure 1: *Total loan exposure to green and non-green SMEs in the 2015-2024 panel dataset. Data is structured at the firm level so that "Loans to green SMEs" also includes their non-green loans. No data available for the share of green loans in 2015 and 2016.*

Figure 2 provides us with a closer view of the use of proceeds underlying the green portfolio. The three green subcategories are unequally distributed throughout our panel. The most prevalent category is energy efficiency, but its relative share decreases from around 75% in 2015 to below 55% by 2024. Loans in this category finance investments in machinery, equipment, devices, or buildings with the aim of reducing energy use or CO_2 emissions by at least 20%, either in absolute or relative terms. The baseline for comparison can be a national/regional efficiency standard or the firm's historical consumption and it includes greenfield projects, expansions, replacements, and refurbishments. The most common loans (around 70%) in this category finance energy-efficient production machinery and equipment. This can include investments as diverse as machinery for harvesting and processing of agricultural goods, CNC machines, production lines, as well as compressors and pumps. Other relevant investments in this category include energy-efficient buildings and insulation, as well as energy-efficient and electric vehicles (for more details on the green subcategories, see figures A1-A3 in the Appendix).

Renewable energy has become more prevalent in the last four years of the dataset, with a final share of 23% of green SME loans. Such loans fund the generation of energy from renewable sources, such as solar photovoltaics (PV), biomass, and biogas, for either own consumption or for feeding into the grid. As our database covers balance sheet lending to SMEs and excludes project

finance loans, more than 85% of the renewable energy loans in our dataset are for small-scale (< 1 MW) field or rooftop PV systems, which primarily produce energy for self-consumption.

Finally, green measures constitute the main use of proceeds from loans for around 25% of green SMEs. Such loans finance measures that reduce pollution, improve resource efficiency, or support environmentally beneficial activities. This category encompasses a diverse range of investments, with the most prominent being loans for vehicles with reduced air pollution (<30%) and the financing of companies operating in sustainable sectors, such as sustainable energy or recycling (>20%). It also includes loans to SMEs producing sustainable, certified products, such as those in organic agriculture (>10%), as well as loans for soil-protecting measures, including no-till or mini-till agricultural machinery (>5%).

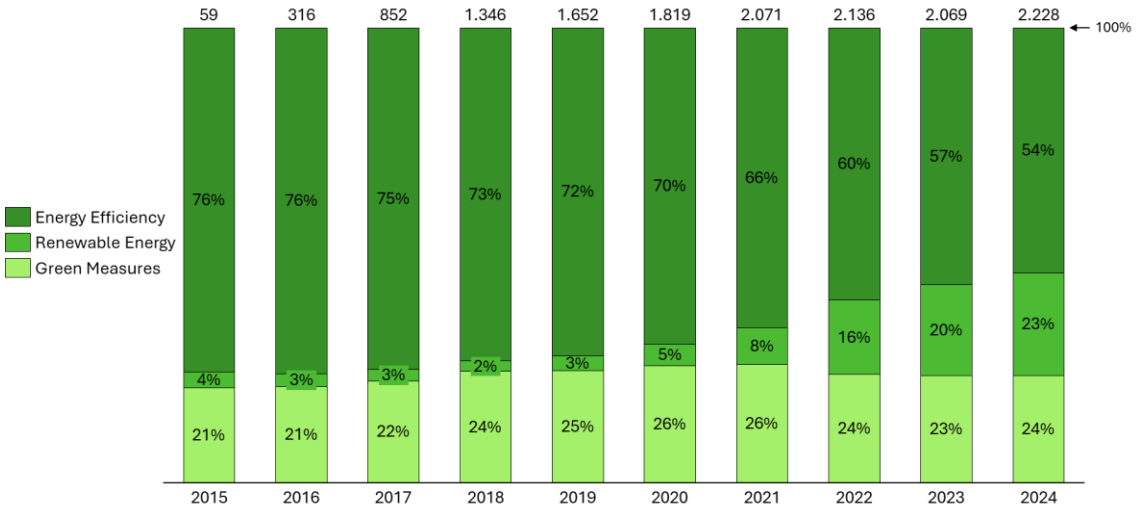


Figure 2: *Breakdown of the loan exposure to green SMEs into three green use of proceeds subcategories. If one green SME qualifies for two green subcategories, its loan exposure is distributed evenly among both green subcategories.*

5.2 Main Model Results

Table 3 presents the fixed effects estimates of the baseline regressions outlined in Section 4. We find a significant negative and economically substantive effect of green SMEs on the probability of default compared to non-green SMEs across all specifications. Our first specification shows the main model with firm and year fixed effects. After controlling for all observable factors, green borrowers experienced a 0.95 percentage point decrease in their default probability. Given the

average default rate of 6.07% non-green SMEs (see Table 1), this represents an economically meaningful relative reduction in the default probability of 15.7%.

In our second specification, we replace the binary green indicator with the continuous green share of total SME exposure. The results reveal a statistically significant negative association between the intensity of green lending and default risk. A 25-percentage point increase in the share of green financing within an SME is associated with a 0.33 percentage point lower probability of default, which corresponds to a 5.4% relative reduction. This finding suggests a dose–response relationship, whereby default risk declines as green exposure increases.

In our third specification, we investigate heterogeneous effects for different uses of proceeds: energy efficiency, renewable energy, and green measures. We find that the reduction in default probability applies only to SMEs that receive loans for energy efficiency and renewable energy. Namely, the risk-reducing effect observed is three times stronger for renewable energy (2.4pp) than for energy efficiency (0.8pp) financing. This corresponds to a 39.7% reduction of default probability for renewable energy financing and a 13.2% reduction for energy efficiency financing.

Specifications 4, 5, and 6 replicate the regressions using the matched and weighted sample, resulting in a reduced number of observations. The point estimates remain negative across all specifications, though there are changes in statistical significance. Green SMEs and renewable energy financing continue to show statistically significant effects at the 1% level, while energy efficiency financing becomes significant at the 5% level. However, the green share of total exposure is no longer statistically significant in the matched sample. The magnitude of the significant point estimates remains very similar, with only a 0.1pp reduction in the estimate of the energy efficiency effect. However, the baseline default rate of the matched non-green firms is only 5.76%, resulting in larger relative effects (16.3% for green SMEs, 12.5% for energy efficiency, and 42% for renewable energy). Despite these slight variations in significance and magnitude, the consistency of the results across both the unmatched and matched samples reinforces the robustness of the findings. The only exception is the dose–response relationship between the green share and default risk, which could not be consistently confirmed across all specifications.

Table 3: *Regression Models*

VARIABLES	(1) default	(2) default	(3) default	(4) default	(5) default	(6) default
Green SME	-0.0095***			-0.0094***		
	[0.0020]			[0.0030]		
Green share		-0.0132***			-0.0053	
		[0.0030]			[0.0042]	
Energy Efficiency			-0.0083***			-0.0072**
			[0.0022]			[0.0033]
Renewable Energy			-0.0241***			-0.0242***
			[0.0028]			[0.0044]
Green Measures			-0.0026			-0.0036
			[0.0031]			[0.0040]
Risk Rating	0.0282***	0.0282***	0.0281***	0.0256***	0.0256***	0.0255***
	[0.0010]	[0.0010]	[0.0010]	[0.0019]	[0.0019]	[0.0019]
Green SME x Risk Rating						
Loan Size (ln)	-0.0020***	-0.0021***	-0.0020***			
	[0.0002]	[0.0002]	[0.0002]			
Firm Tenure	0.0128***	0.0129***	0.0129***			
	[0.0004]	[0.0004]	[0.0004]			
Max Maturity	0.0000	0.0000	0.0000			
	[0.0000]	[0.0000]	[0.0000]			
Fixed Assets	0.0006	0.0006	0.0006			
	[0.0025]	[0.0025]	[0.0025]			
Working Capital	-0.0021	-0.0021	-0.0021			
	[0.0024]	[0.0024]	[0.0024]			
Constant	-0.1010***		-0.1013***	-0.0979***	-0.1005***	-0.0989***
	[0.0052]		[0.0052]	[0.0091]	[0.0053]	[0.0091]
Observations	172,591	172,591	172,591	43,003	43,003	43,003
R-squared	0.061	0.061	0.061	0.055	0.054	0.055
Number of firms	43,063	43,063	43,063	9,934	9,934	9,934
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Finally, we test for heterogeneous treatment effects in the green–default relationship to better understand the differential risk dynamics of green and non-green SMEs along the risk spectrum.

Allowing the effect of green status to vary with the firm's internal risk rating reveals substantial heterogeneity in the green–default relationship. The interaction between green status and the risk rating is negative and statistically significant, implying that the marginal effect of the green status on default probability becomes increasingly negative for riskier SMEs (Table A3 in the Appendix). As shown in Figure 3, while no significant effect is observed for the safest firms (risk ratings 1 & 2), green status is associated with sizable reductions in default probability at higher risk levels (starting at risk rating 3). This pattern remains robust when repeated in the matched sample, indicating that the results are not driven by observable differences between green and non-green firms. This supports the interpretation that SMEs receiving green loans are associated not only with lower risk on average, but also with heterogeneous risk dynamics along the risk spectrum. Interestingly, green SMEs do not have better average risk ratings (see Table 1), which suggests that incorporating green status as a risk predictor could enhance the bank's risk quantification model's forecasting capabilities.

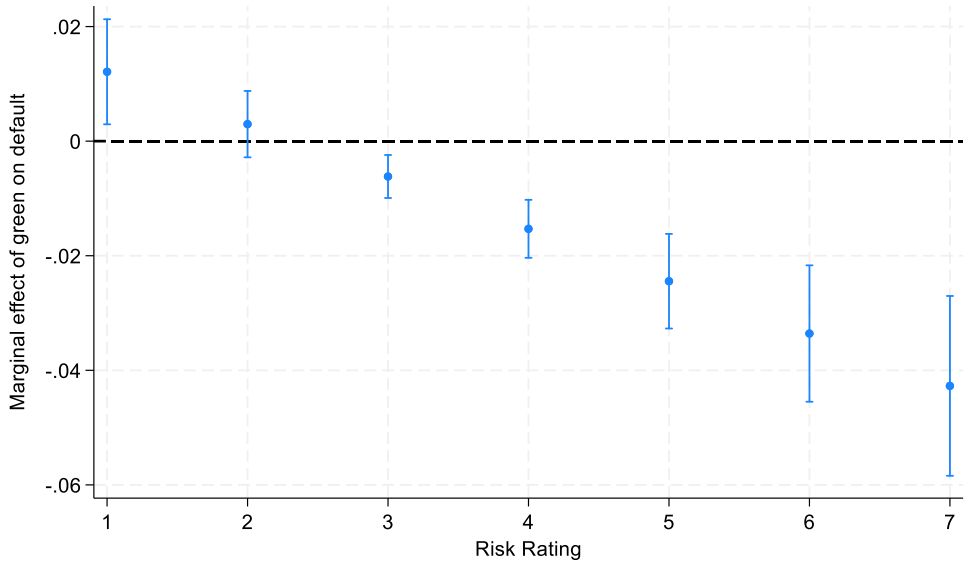


Figure 3: *Marginal effect of switching from non-green to green on SME default probability evaluated at each risk rating in the unmatched sample (see Figure A4 in the Appendix for the matched sample).*

5.3 Robustness Checks

A potential limitation of our baseline models is our reliance on the bank's internal risk rating, which aggregates both quantitative and qualitative firm characteristics. To address this, we conduct

a robustness check by replacing the internal risk rating with three key indicators of financial distress that are commonly used in SME credit risk assessment (Ciampi et al., 2021): Return on average assets (RoAA) to measure profitability, the debt-to-EBITDA ratio (earnings before interest, taxes, depreciation and amortization) to measure leverage and payment capacity, and current ratio (current assets/current liabilities) to assess liquidity (see Table 1). As shown in Table A4 in the Appendix, the results remain consistent with the baseline findings. Specifically, RoAA and debt-to-EBITDA are statistically significant and exhibit the expected signs, while the current ratio is not significantly different from zero, suggesting limited explanatory power in predicting default risk.

Another potential concern is our model choice. As discussed in Section 2, prior literature on micro-level mortgage data typically employs survival models, such as the Cox proportional hazard model, to estimate default differentials between green and non-green loans. In Table A5 in the Appendix, we present the results from applying a Cox proportional hazard model to our sample. The findings confirm the robustness of our results, showing that green SMEs exhibit a hazard ratio of 0.67 ($p < 0.001$), which implies that green SMEs have a 33% lower default hazard compared to non-green SMEs, after controlling for internal risk rating, firm and loan characteristics, sector, year, and time effects. Furthermore, we observe that a one-unit increase in the internal risk rating more than doubles the default hazard, validating the effectiveness of our primary control variable.

6. Discussion

One possible explanation for the results of our empirical analysis is that the observed reduction in default risk is driven by lower energy costs and reduced dependency on volatile energy prices. This interpretation aligns with the results of Billio et al. (2022), who found that an increase in disposable household income led to a decrease in mortgage default rates for energy-efficient homes. Our findings suggest that the reduced default risk may be due to lower energy costs resulting from green investment and the subsequent increase in disposable income. This causal mechanism could also explain why the risk-reducing effect is most pronounced for renewable energy loans, which directly lower energy consumption from the grid, followed by energy efficiency loans, defined as those achieving relative energy savings of at least 20%. Conversely, green measures, which can relate to pollution and other impacts independent of energy consumption, were found to have no statistically significant effect on the probability of default.

Furthermore, this causal mechanism may help explain the identified heterogeneous risk dynamics. The inherent volatility of energy prices represents a significant downside risk for many SMEs, which could be effectively mitigated through energy-related green investments. As a result, SMEs in financial distress stand to benefit the most, with these investments offering a stronger shield against the financial uncertainty caused by fluctuating energy costs.

Therefore, our findings demonstrate the potential hedging effect of on-site energy generation and efficiency improvements against energy price fluctuations for SMEs, resulting in reduced default probabilities. Studies with more extensive data on firm characteristics and those employing more rigorous evaluation methods should test the potential causal effects driving the risk differential.

A second possible explanation for the results is that they are not caused by the green investment itself, but rather that green serves as a visible marker for other unobserved factors that affect the default risk. Given that our fixed-effects design controls for all time-invariant unobservables, such unobserved factors would need to be time-varying and correlated with SMEs taking up green loans. For example, a new generation taking over the management of family businesses, bringing greater entrepreneurial foresight, may be more inclined to invest in sustainable technologies. Similarly, the period before and during the European Green Deal provided extensive support and subsidy programs for green SMEs, potentially enhancing their performance independently of the investment itself. In both cases, the green classification could act as a proxy for otherwise unobservable firm-, market-, or policy-related characteristics rather than capturing the direct financial effect of the investment.

A third potential explanation does not focus on the SMEs themselves but rather on the underwriting institution and its staff. As discussed in Section 3.1, ProCredit Group has developed and implemented a comprehensive green lending strategy, accompanied by extensive training and supported by external consultants. It can therefore be assumed that this institutional emphasis and learning have enhanced the underwriting skills of the responsible staff in assessing green investments compared to non-green investments, which in turn could also contribute to the findings of this study. This will be especially true for green loans that cannot be automatically categorized but require individual assessment, either due to complexity or size. Such cases simply received more scrutiny than non-green loan applications, which could then contribute to the improved performance. This line of argumentation could be helpful in interpreting the findings of

Zhou et al. (2022), who found that smaller Chinese banks saw a worsening, while big state banks saw an improvement in credit risk indicators when increasing their share of green lending. If the link from green lending to an improved credit risk performance depends on the quality of staff and the investments in training, it would explain why larger banks were more successful than smaller banks that had fewer resources available to comply with the China Green Finance Policy.

These three potential causal mechanisms are not mutually exclusive and could therefore all contribute to the observed effects; however, only the first one can explain the observed heterogeneous effects between energy-related and other green investments. Independent of the exact causal mechanisms underlying the observed risk-reducing effect of green SME lending, the identified reduction in default risk has implications for both the banking industry and the green transition of SMEs. On an industry level, these results support sustainability front-runners by demonstrating how sustainability-oriented banking can also yield financial benefits. For banks, the reduced probability of default translates into lower provisions and write-offs, and consequently, into an increased risk-adjusted margin. If these benefits in risk reduction exceed the investments required to implement and maintain a bank's green lending strategy, they enhance the bank's overall profitability while also improving its risk management. The analyzed case also illustrates how financial and technical assistance from IFIs and development institutions to banks for the establishment of a green lending strategy may create long-term financial benefits for these banks and SMEs beyond the desired societal and environmental effects.

When it comes to credit risk modeling, this study demonstrates that incorporating the green classification into a bank's credit risk model can capture statistically significant and economically meaningful dynamics of the default probability of SMEs. Given that most banks currently do not incorporate sustainability or green metrics at the firm or loan level into their risk quantification models, the predictive capabilities of these models could likely be enhanced. The identified link between green and credit risk in SME lending can also be relevant for SME-financing banks that need to comply with the recent EBA guidelines (EBA, 2025) requiring them to consider ESG risk aspects in their credit decision making process.

On a regulatory level, these results can inform policymakers and regulators in their efforts to better understand the relationship between green financial regulation and financial stability. The study contributes to the growing body of research that demonstrates the importance of non-financial ESG

data in explaining dynamics within the financial system (Ziolo et al., 2019). The results contradict the argument that financial regulation in favor of environmental aspects would lead to a misallocation of capital and risk ("green bubble argument"), and instead provide empirical support for green central bank policies and other green financial market regulatory reforms. Our findings suggest that incorporating the observed risk differential into bank risk quantification and pricing models could improve financial market efficiency.

The most relevant implication of our results is for the green transition of SMEs. If the observed risk differential were to be reflected in banks' risk and pricing models or in financial regulation and subsequently bank capital costs (for example by differentiating between green and non-green in the SME supporting factor in the Capital Requirements Regulation), it would improve the availability and cost of capital of green loans as compared to non-green loans and could significantly speed up the decarbonization of the important SME segment.

7. Conclusion

This paper examines whether there is empirical evidence of a credit risk differential between green and non-green SMEs, based on a 10-year panel comprising over 43,000 SMEs across 11 countries. Its first contribution is publishing relevant descriptive insights into the green lending potential for the SME segment, making visible which investment categories underlie the green label and how they are distributed across economic sectors. Furthermore, we show that SMEs receiving financing labeled as green experience an average reduction in their default probability of around 16%. When delving deeper into the heterogeneous effects analysis, our study shows that SME financing of energy efficiency and renewable energy investments reduced the respective default probabilities by 13% and 40% while other green measures did not have a statistically significant risk-reducing effect. We further show that green lending seems to have a dose-response relationship with default, and that SMEs with riskier financial indicators benefit more from the risk-reducing effect than financially stronger SMEs. The results are robust across various model specifications, including fixed effects regressions, matching methods and a Cox proportional hazard model.

Our findings suggest that the incorporation of the observed risk differential in bank risk quantification and pricing models could improve financial market efficiency while simultaneously improving the availability and cost of capital of green loans, which would have far-reaching implications regarding the availability and pricing of green loans and could significantly speed up

the decarbonization of the SME segment. Our results confirm existing research on green differentials in risk and pricing in other asset classes, but they present the first empirical study confirming these findings in the SME segment.

Further research should focus on collecting data from a larger number of banks and include a broader range of countries to test the external validity of the results presented in this paper. Once the green classification systems are harmonized within the industry, results from previous studies can be verified and compared against one another.

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Appendix

Table A1: *List of eligible green investments used by ProCredit Group*

- EE Energy Efficiency
  - EE1 Building envelope
    - EE1.1 Insulation of exterior walls
      - EE1.1.0 Insulation of exterior walls - old aggregated
      - EE1.1.1 Insulation of exterior walls
    - EE1.2 Insulation of roofs, attic floors or terraces
      - EE1.2.0 Insulation of roofs, attic floors or terraces - old aggregated
      - EE1.2.1 Insulation of roofs, attic floors or terraces
    - EE1.3 Insulation of ground floor, foundations and basement
      - EE1.3.0 Insulation of ground floor, foundations and basement - old aggregated
      - EE1.3.1 Insulation of ground floor, foundations and basement
    - EE1.4 Double/triple glazed windows
      - EE1.4.0 Double/triple glazed windows - old aggregated
      - EE1.4.1 Double/triple glazed windows
    - EE1.5 Doors, automatic doors and shutters
      - EE1.5.0 Doors, automatic doors and shutters - old aggregated
      - EE1.5.1 Doors, automatic doors and shutters
    - EE1.6 Building envelope – combined measures
      - EE1.6.0 Building envelope – combined measures - old aggregated
      - EE1.6.1 Building envelope – combined measures
    - EE1.7 Building envelope – energy efficient buildings
      - EE1.7.0 Building envelope – energy efficient buildings - old aggregated
      - EE1.7.1 Building envelope – energy efficient buildings
  - EE2 Heating, cooling, ventilation and air conditioning (HVAC)
    - EE2.1 Space cooling
      - EE2.1.0 Space cooling - old aggregated
      - EE2.1.1 Air conditioning units (split and mini split)
      - EE2.1.1 Air conditioning units (centralized)
      - EE2.1.3 Ventilation systems
      - EE2.1.4 Chillers and cooling towers
      - EE2.1.5 Other (incl. BMS)
    - EE2.2 Space heating
      - EE2.2.0 Space heating - old aggregated
      - EE2.2.1 Heat pumps (air based)
      - EE2.2.2 Burner/heating boilers
      - EE2.2.3 Heating stoves
      - EE2.2.4 Central heating systems
      - EE2.2.5 Other
    - EE2.3 Processes – heating and cooling
      - EE2.2.0 Processes – heating and cooling - old aggregated
      - EE2.3.1 Cooling chamber and chillers
      - EE2.3.2 Steam Boiler
      - EE2.3.3 Waste heat recovery

- EE2.3.4 Other
- EE3 IT equipment white goods
  - EE3.1 IT Equipment
    - EE3.1.0 IT equipment - old aggregated
    - EE3.1.1 Computer and auxiliary equipment
    - EE3.1.2 Green IT Systems and servers
  - EE3.2 White goods – domestic and commercial appliances
    - EE3.2.0 White goods – domestic and commercial appliances - old aggregated
    - EE3.2.1 Refrigerators
    - EE3.2.2 Freezers
    - EE3.2.3 Washing machines
    - EE3.2.4 Dryers
    - EE3.2.5 Cooking equipment (ovens/stoves)
- EE4 Lighting
  - EE4.0 Lighting - old aggregated
  - EE4.1 Interior lighting improvements
  - EE4.2 Exterior lighting improvements
- EE5 Production and processes
  - EE5.1 Production machinery and equipment (excluding agriculture)
    - EE5.1.0 Production machinery and equipment (excluding agriculture) - old aggregated
    - EE5.1.1 CNC machine (wood)
    - EE5.1.2 CNC machine (metal)
    - EE5.1.3 CNC machine other
    - EE5.1.4 Printing machines
    - EE5.1.5 Ovens (convection, induction, food processing)
    - EE5.1.6 Pumping systems
    - EE5.1.7 Electric motors and drives
    - EE5.1.8 Compressed air systems/Compressors
    - EE5.1.9 Cutting machines and saws
    - EE5.1.10 Packaging and bottling machines
    - EE5.1.11 Cleaning equipment (clean in place system, washing system, etc.)
    - EE5.1.12 Injectors
    - EE5.1.13 Extruders
    - EE5.1.14 Lathe machine
    - EE5.1.15 Drilling machines
    - EE5.1.16 Welding machines
    - EE5.1.17 Autoclaves and sterilization equipment (for medical and food processing use)
    - EE5.1.18 Presses
    - EE5.1.19 Garment and Textile processing machines (sewing, embroidery, cutting, knitting, dying, blowers, spinning, etc.)
    - EE5.1.20 Milk processing equipment (e.g. pasteurization, mixers)
    - EE5.1.21 Other food processing equipment (mixer, blenders, cutters, grinders, smokers, feeders, cookers, blanchers, etc.)
    - EE5.1.22 Other metalworking machinery
    - EE5.1.23 Other wood processing machines (lathe, drilling, etc.)
    - EE5.1.24 Other plastic machinery

- EE5.1.25 Reactive power compensators
- EE5.1.26 Other
- EE5.2 Production machinery, equipment and systems for agriculture
  - EE5.2.0 Production machinery, equipment and systems for agriculture - old aggregated
  - EE5.2.1 Tractors
  - EE5.2.2 Harvesters
  - EE5.2.3 Multi-stage agricultural equipment
  - EE5.2.4 Milking equipment
  - EE5.2.5 Efficient irrigation system (pumps)
- EE6 Transport
  - EE6.1 Fuel-efficient vehicles
    - EE6.1.0 Fuel-efficient vehicles - old aggregated
    - EE6.1.1 Electric vehicles (EV)
    - EE6.1.2 Plug-in hybrid vehicles
    - EE6.1.3 New alternative fuel systems vehicles (e.g. fuel cells)
- EE7 Other
  - EE7.1 Other

RE Renewable Energy
- RE1 Solar water heating systems
  - RE1.1 Solar water heating systems
- RE2 Photovoltaic systems (PV)
  - RE2.0 PV systems - old aggregated
  - RE2.1 PV field installations
  - RE2.2 PV rooftop or facade installations
- RE3 Hydro-power plants
  - RE3.1 Hydro-power plants
- RE4 Wind power systems
  - RE4.1 Wind power systems
- RE5 Geothermal systems
  - RE5.1 Geothermal heat production
  - RE5.2 Geothermal electricity production
- RE6 Biomass energy / biogas plants
  - RE6.1 Biogas plants
  - RE6.2 Biomass
    - RE6.2.0 Biomass - old aggregated
    - RE6.2.1 Co-generation biomass plants (power and heat)
    - RE6.2.2 Pellet, wood or bio-waste boilers (only heat)
- RE7 Other
  - RE7.1 Other

GR Environmental Measures
- GR1 Environmental protection
  - GR1.1 Soil protection measures
    - GR1.1.0 Soil protection measures - old aggregated
    - GR1.1.1 Mini till seeding
    - GR1.1.2 Restoration of the terrain
    - GR1.1.3 Forestation
    - GR1.1.4 Embarkment reinforcement

- GR1.1.5 Impervious sealing for chemical storage
- GR1.1.6 Other
- GR1.2 Air protection measures - purification systems
- GR1.3 Air protection measures - low pollutant vehicles
  - GR1.3.0 Air protection measures - low pollutant vehicles - old aggregated
  - GR1.3.1 Air protection measures – Lower emission heavy duty transport
  - GR1.3.2 Air protection- Fuel switch of vehicles
  - GR1.3.3 Air protection measures - Lower emission non-road vehicles (telehandlers)
  - GR1.3.4 Air protection measures - Lower emission non-road vehicles (harvesters)
  - GR1.3.5 Air protection measures - Lower emission non-road vehicles (construction vehicles)
  - GR1.3.6 Air protection measures - Lower emission non-road vehicles (other)
- GR1.4 Water protection measures
  - GR1.4.0 Water protection measures - old aggregated
  - GR1.4.1 Wastewater treatment plants
  - GR1.4.2 Irrigation systems (in terms of saving water needed for the irrigation)
  - GR1.4.3 Closed cooling water system
  - GR1.4.4 Water harvesting
  - GR1.4.5 Other

GR2 Recycling, prevention of waste, waste management
- GR2.1 Recycling, prevention of waste, waste management
  - GR2.1.0 Recycling, prevention of waste, waste management - old aggregated
  - GR2.1.1 Recycling
  - GR2.1.2 Prevention of waste production
  - GR2.1.3 Waste management (incl. Equipment and incinerators)

GR3 Services for the environmental/ energy sector
- GR3.1 Services for energy sector
  - GR3.1.0 Services for energy sector - old aggregated
  - GR3.1.1 Energy audits
  - GR3.1.2 Energy consultancy
  - GR3.1.3 ESCOs (Energy Service Companies)
- GR3.2 Services for the environmental sector
  - GR3.2.0 Services for the environmental sector - old aggregated
  - GR3.2.1 Consultation and planning services aimed at preventing environmental pollution
  - GR3.2.2 Environmental licensing
  - GR3.2.3 Environmental certification

GR4 Sustainable certified products
- GR4.1 Sustainable certified products
  - GR4.1.0 Sustainable certified products - old aggregated
  - GR4.1.1 Organic certified products
  - GR4.1.2 Certified products made from sustainable materials - eco labels

GR5 Supply-side: suppliers / producers of EE/RE/GR materials and equipment
- GR5.1 Suppliers / producers / services for the EE sector
- GR5.2 Suppliers / producers / services for the RE sector

GR5.3 Suppliers / producers / services for environmental protection technologies

GR6 Resource efficiency

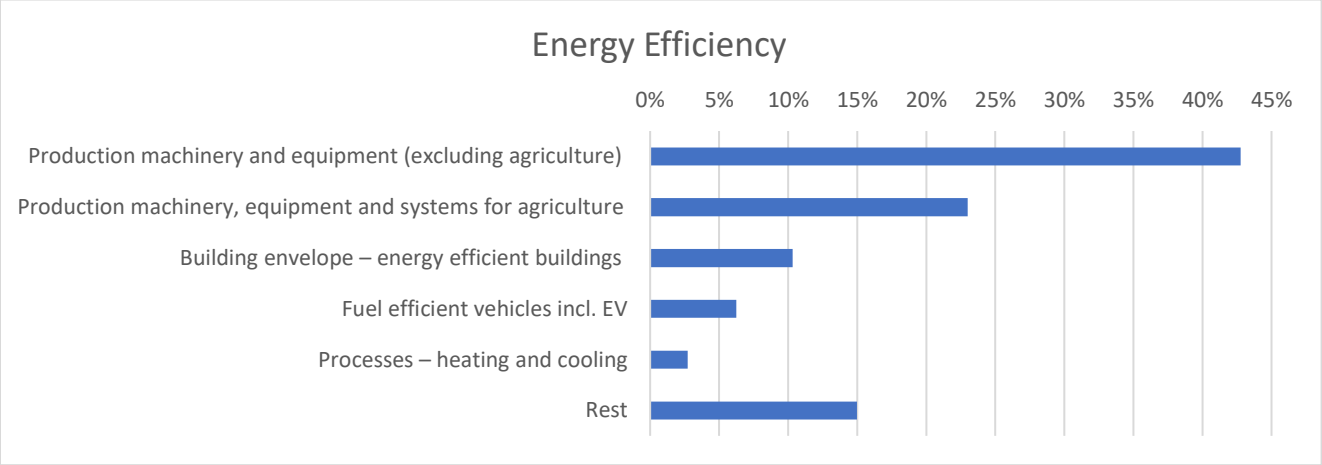


Figure A1: *Energy efficiency observations in the panel*

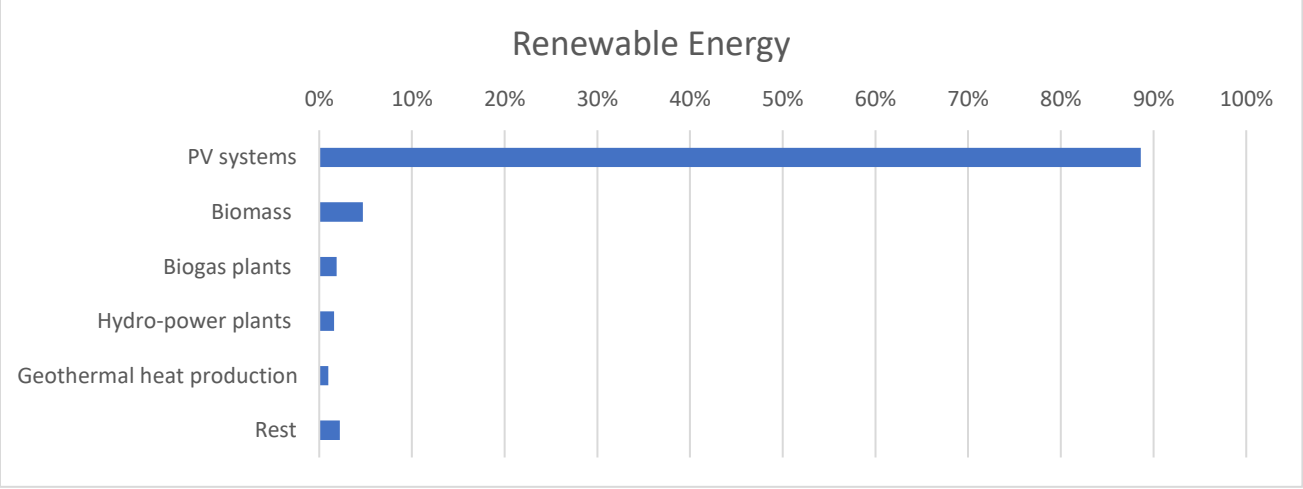


Figure A2: *Renewable energy observations in the panel*

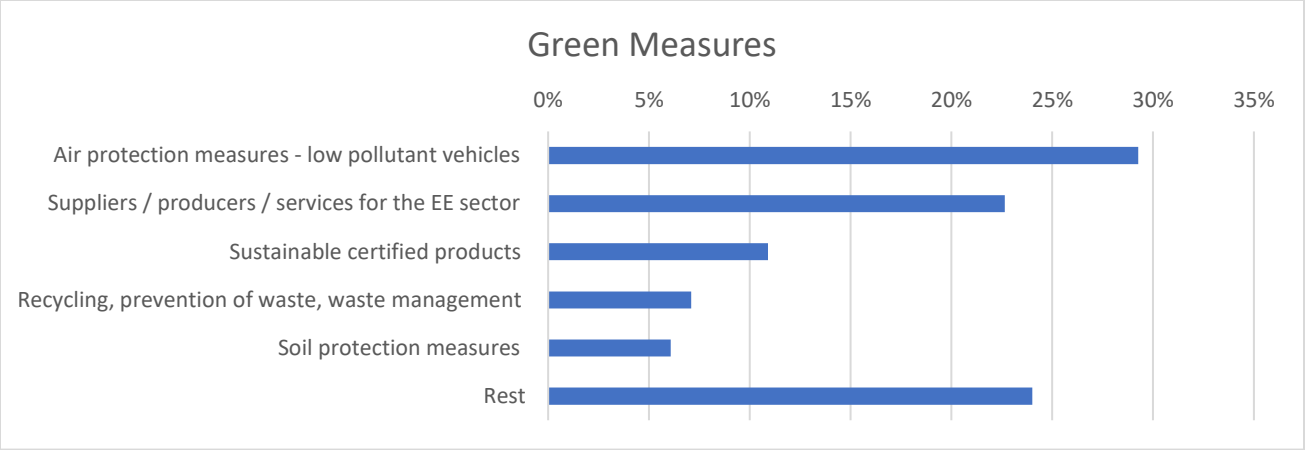


Figure A3: *Green measures observations in the panel*

Table A2: *Total loan exposure and green share per economic sector 2017-2025*

ISIC Economic Activity	Loan Portfolio in million EUR	Green Share
N/A - Not Available	69.4	5.0%
A - Agriculture, forestry and fishing	7,246.9	15.2%
B - Mining and quarrying	103.0	13.9%
C - Manufacturing	8,813.7	23.5%
D - Electricity, gas, steam and air conditioning supply	153.1	70.1%
E - Water supply; sewerage, waste management and remediation activities	165.8	55.4%
F - Construction	2,301.9	20.7%
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	10,281.8	9.6%
H - Transportation and storage	1,892.8	15.0%
I - Accommodation and food service activities	1,260.7	18.7%
J - Information and communication	402.5	12.3%
K - Financial and insurance activities	4.4	4.3%
L - Real estate activities	1,034.4	11.0%
M - Professional, scientific and technical activities	487.3	17.1%
N - Administrative and support service activities	454.5	11.4%
O - Public administration and defence; compulsory social security	5.1	3.5%
P - Education	282.5	19.1%
Q - Human health and social work activities	410.8	13.4%
R - Arts, entertainment and recreation	74.5	37.0%
S - Other service activities	106.0	8.2%
T - Activities of households as employers	117.0	7.3%
Total	35,668.0	16.3%

Notes: 2017-2025 as the time period chosen due to data quality issues for green share in 2015 and 2016.

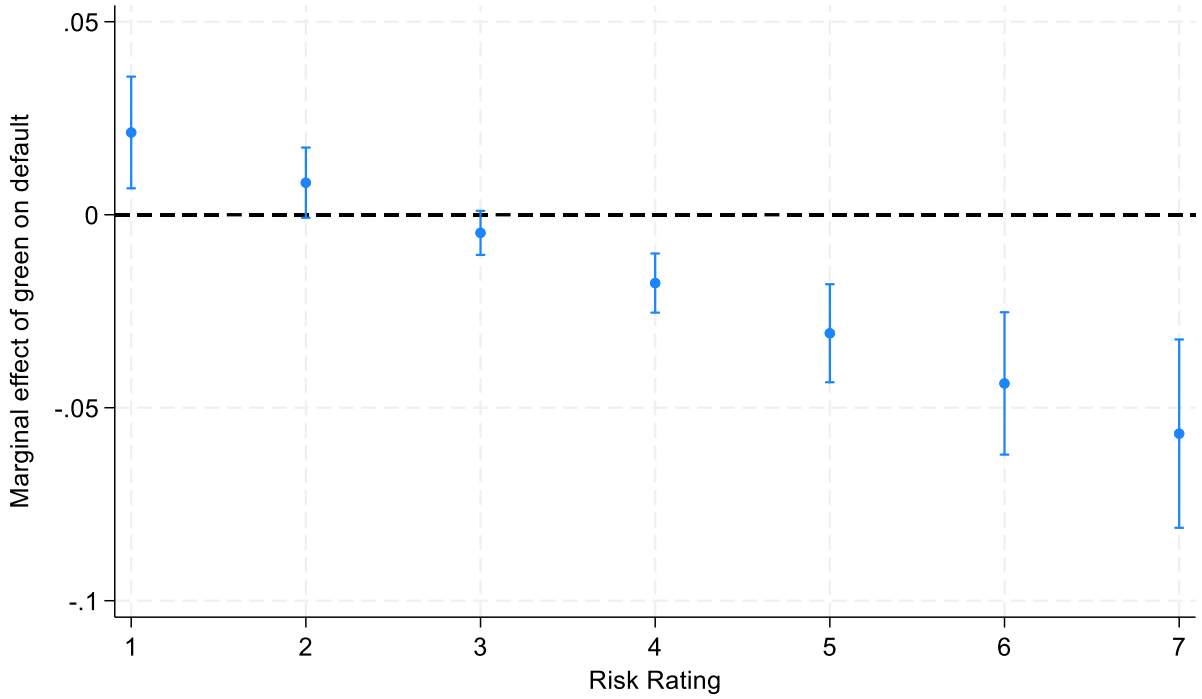


Figure A4: *Marginal effect of switching from non-green to green on SME default probability evaluated at each risk rating in the matched sample.*

Table A3: *Green SME - risk rating interaction effect*

VARIABLES	(1) Matched sample default	(2) Unmatched sample default
Green SME	0.0343***	0.0212***
	[0.0104]	[0.0066]
Risk Rating	0.0312***	0.0299***
	[0.0027]	[0.0012]
Green SME x Risk Rating	-0.0130***	-0.0091***
	[0.0032]	[0.0020]
Loan Size (ln)		-0.0020***
		[0.0002]
Firm Tenure		0.0132***
		[0.0004]
Max Maturity		0.0000
		[0.0000]
Fixed Assets		0.0006
		[0.0025]
Working Capital		-0.0020
		[0.0024]
		0.0217***
		[0.0027]
Constant	-0.1168***	-0.1066***
	[0.0110]	[0.0055]
Observations	43,003	172,591
Number of firms	9,934	43,063
R-squared	0.057	0.062
Firm FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A4: *Robustness checks*

	Fixed Effects	Cox proportional hazard
VARIABLES	default	_t
_t		.
		[.]
Green SME	-0.0092***	0.6607***
	[0.0021]	[0.0345]
RoAA	-0.0035***	
	[0.0009]	
Debt/EBITDA	0.0047***	
	[0.0005]	
Current Ratio	0.0005	
	[0.0005]	
Risk Rating		2.0685***
		[0.0248]
Loan Size (ln)	-0.0016***	1.0371***
	[0.0002]	[0.0072]
Firm Tenure	0.0122***	1.0061
	[0.0005]	[0.0043]
Max Maturity	0.0000	0.9986***
	[0.0000]	[0.0005]
Fixed Assets	-0.0009	0.9082*
	[0.0028]	[0.0476]
Working Capital	-0.0042	0.8639***
	[0.0027]	[0.0477]
Constant	-0.0365**	
	[0.0171]	
Observations	130,247	166,953
Number of firms	26,862	
R-squared	0.035	
Firm FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1