GREEN FIRMS ARE LESS RISKY: RESULTS FROM A PREFERENTIAL CAPITAL REQUIREMENT PROGRAM IN EMERGING EUROPE

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Abstract

This paper assesses the credit risk of sustainable loans in a preferential capital requirement program. We exploit loan-level data from a unique implemented program from Hungary using logistic regressions and survival analysis techniques. We find significantly lower risk for firms with renewable energy and electromobility loans, even after controlling for all relevant factors. These results are economically significant and robust for modelling choices, different identification of green firms and default definition too. We show that green loans' lower probability of default can imply a discount of several percentage points in capital requirements.

JEL classifications: E58, G21, G33, O16

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1.1. Introduction

Climate change became a primary concern for central banks and supervisor authorities too (Burger and Wójcik, 2023). Various forms of monetary policy instruments and prudential regulation tools were identified to promote green finance. Some emphasized that any climate policy by central banks should be designed carefully to avoid unintended trade-offs with their core mandates (Diluiso et al., 2021). Others argued that encouraging sustainable finance is also the central banks' legal obligation, since more than half of the central banks have direct or indirect sustainability mandates (Dikau & Volz, 2021). Several policy actions were recommended, such as quantitative easing (QE) programs, which limit the impact of climate change on financial stability (Dafermos et al., 2018), or the introduction of green macroprudential policy tools, which counterbalance the ineffectiveness of the current carbon pricing regimes in directing funding towards low-carbon activities (Campiglio, 2016).

One potential tool for central banks to promote transition to a low-carbon economy is to fine-tune capital requirements regulations by implementing green supporting factors (GSF) and dirty penalizing factors (DPF). A GSF reduces the minimum amount of capital required to be held for exposures which are considered green. By contrast, DPF prescribes higher capital buffers for loans to corporates with high GHG emissions. The simultaneous use of GSF and DPF may neutralize changes to the banking sector's overall capital requirements. The net effect of such changes may tilt funding towards sustainable activities therefore help to achieve transition to a climate friendly economy.

Since the main goal of capital requirements is to stabilize financial institutions, these requirements are risk based. Consequently, the main argument in favour of a GSF would be that green exposures are less risky than others. Firstly, this hypothesis is mainly based on the lower level of transition risks for sustainable loans. Secondly, firms with green loans signal an environmentally conscious management attitude and capability to obtain such complex products, which can improve credit performance as well. Additionally, some studies found that sustainable firms have better financial performance than their peers and ESG scores improve credit worthiness (Brogi & Lagasio, 2018; Carbone et al., 2021).

Although the debate about introducing such green tools to the microprudential framework started several years ago, their little actual experimentation took place. To the best of our knowledge, the green preferential capital requirement program (GPCR) of the Central Bank of Hungary (MNB) has been the only implementation, at the time of writing.

In this paper, we assess the riskiness of loans eligible to the GPCR of the MNB, and compare them to loans with similar characteristics not included in the program. We distinguish between renewable energy (RE) loans and electromobility (EM) loans, use granular, loan level information, and complement this with the profile of the creditor firms from their financial reports. The analysis focuses on the period between 2020 and 2023. We investigate default risk using logistic regression-based default probability (PD) models and time-to-event (survival) models. In a second step, we calibrate the fair level capital requirement for green exposures using our estimates for the risk differential of green and non-green firms.

Our findings confirm that both renewable energy and electromobility loans included in the green preferential capital requirement program of the Central Bank of Hungary exhibit lower PD values than of their peer groups. At the same time, the PD difference explains around half or more of the capital requirement discount, based on a simplified fair capital requirement calculation, based on the formula recommended by Vasicek (2002).

Our paper is closely related to the literature examining the risk differential of green and brown activities. However, there are material data gaps in sustainable finance, there are few studies based on granular data in the corporate segment. Using micro-evidence from Romania between 2010 and 2020 Neagu et al. (2024) assessed credit risk of green loans. They used sustainable indicators identified ex-post by the reporting financial institutions. Their results suggest that green loans bear less credit risk overall, but do not observe a significant risk reduction in the case of green loans if relevant factors are controlled for. Other results in the corporate segment are based on aggregated data. Carbon-neutral lending to corporates improves asset quality of banks due to the lower volatility of the borrowers' earnings (Umar et al., 2021) and higher proportion of green loans reduces banks' NPL ratios (Cui et al., 2018). On the retail side, the lower default risk of residential mortgages financing energy efficient housing was proven in many real estate markets (Kaza et al., 2014; Guin & Korhonen, 2020; Billio et al., 2022). Higher energy use at loan-backed commercial properties increases default rates too (Mathew et al., 2021).

We also contribute to the growing literature on potential tools for central banks and supervisory activities, focusing on green microprudential measures and their effects. The empirical results on the impacts of GSF or DPF introductions are meagre. One paper by Miguel et al (2022) reports on the inclusion of environmental risks in the ICAAP regulation of large banks in Brazil in 2017., The Central Bank of Brazil implicitly introduced a DPF like instrument to loans with higher environmental risks. The authors found that the impacted large banks reallocate their lending away from exposed sectors while also shorten the maturity of loans to these sectors. However, smaller banks, exempt from the regulation, expand their credit supply and the maturity of loans to exposed sectors. They found only moderate impacts to the real economy and to greenhouse gas emissions.

Others focused mainly on theoretical modeling of green microprudential measures. According to Dafermos & Nikolaidi (2021), implementing GSF or DPF slows climate change and thus limits physical risk increases. At the same time, a GSF may increase bank leverage, posing risks to financial stability. The simultaneous implementation of GSF and DPF has the most significant impact on green and dirty investment differences by canceling out real economy and financial stability issues. However, their effects alone are tiny. Optimal regulation may involve complementing GSF with further green finance policies like guarantees, carbon taxation, and carbon risk adjustment (Lamperti et al., 2021; Dunz et al., 2021). Regarding prudential consequences, Oehmke & Opp (2022) found that GSF and DPF are optimal for a prudential mandate, but inefficient for green mandates. Differentiation in capital requirements is proposed to enhance substitution between green and dirty lending.

Our research complements and enhances previous research on empirical risk differential for sustainable firms for multiple reasons, besides assessing the data of another Emerging European country. Firstly, we can estimate our results based on ex ante and differentiated measures of greenness. Financial institutions flagged and reported the loans in real time (every quarter since the beginning of the program) and the reported data were supervised continuously by the central bank. Secondly, banks reported loans that are compliant with the GPCR program. The program's conditions of eligibility are closely following the EU taxonomy, a well-known international standard for sustainability, which gives additional validity to our variables in interests. Thirdly, due to the detailed obligatory reporting scheme of the GPCR, we can differentiate the activities of green firms. We can model the firms with renewable energy production and electromobility related loans differently, and do not have to simplify our research to one group of homogenous "sustainable" firms. Another novelty in the green capital requirement literature is that we are the first to assess the firms to participate in a preferential program in terms of their age, company size and financial indicators. Additionally, we also show the default risk of participating firms overall, and compare to similar but non-participating firms. We are not aware of any calibration results of minimum capital requirement impact akin to ours either, particularly in the sustainability context.

Our research has relevance for policy makers assessing the risk foundation of preferential capital requirements for green loans. In 2022, the European Banking Authority initiated a discussion on how environmental and climate risks could be incorporated into the prudential framework, focusing on Pillar I. The Bank of England also raised the question "whether changes in the design, use or calibration of the regulatory capital framework are needed" (Bank of England, 2021) to tackle climate related financial risks. The evidence on the risk differential between green and non-green loans this paper provides may lead banks to reallocate funding towards green firms to decrease their cost of risk. This is particularly the case if green firms are expected to benefit from future regulation, while non-green may be impacted negatively. Empirical evidence already suggested that this risk channel was a driving force in credit allocation in Europe, and dominated the preference channel (i.e., banks' public commitments) to provide the funding for the green transition (Mueller & Sfrappini, 2022).

The remainder of the paper is structured as follows: Section 1.2 describes the institutional background of the program, Section 1.3 introduces the data sources we use and presents summary statistics. In Section 1.4, we detail the tools for empirical analysis and the formula to calibrate a fair level of capital discount. We present our results and its limitations in Section 1.5. Section 1.6 concludes.

1.2. Institutional background

In 2019, MNB launched a Green Program to "mitigate the risks associated with climate change and other environmental problems, to expand green financial services in Hungary" (MNB, 2019). This program included a broad spectrum of measures, including education and knowledge sharing in green finance, a reduction of its own ecological footprint, as well as the launch of the Green Mortgage Bond Purchase Program and the Green Home Program. The two latter initiatives were launched in 2021, right after the publication of the Green Monetary Policy Toolkit Strategy (MNB, 2021). Not coincidentally, MNB became the first European central bank to be provided with an explicit green mandate. According to the country's Central Bank Act, the MNB is mandated to support environmental sustainability without compromising its primary objective, price stability.

Hungary implements the bank regulation of the EU, which is based on the Basel Committee on Banking Supervision's (BCBS) set of recommendations. In the Basel framework, regulatory capital requirements have three pillars. Pillar I sets capital adequacy requirements detailed in the Capital Requirements Regulation defined by the European Banking Authority, and cover credit, market and operational risks. Pillar II requirements are set by the supervisory authorities during the supervisory review and evaluation process (SREP) to address potential shortcomings and risks not detailed in Pillar I. Supervisors can (and usually do) require additional capital above the level determined by Pillar I. They also provide a non-binding capital expectation guidance in Pillar II. Pillar III aims to foster market discipline, as it obliges banks to disclose additional information on their operations, without directly impacting capital levels. As the supervisory authority in Hungary, it is the MNB that evaluates banks during the SREP process and oversees the setting and auditing of capital requirements.

In December 2020, MNB launched the Green Preferential Capital Requirement Program (GPCR) for sustainable corporate and municipal financing. The program initially covered loans and bonds funding renewable energy assets and green bonds issued in line with the Green Bond Principles or Climate Bonds Standards only, but in August 2021 the list of eligible activities was expanded considerably to include further items (electromobility, sustainable agriculture and food industry, commercial real estate and energy efficiency or acquisition and buy-out of green business equity as well). Qualifying loans must fulfil one of these financing objectives and must be originated after 2020. January 1st. The eligibility criteria for each of the goals above are based on the Hungarian implementation of the EU Taxonomy (considering local data availability and other specialties). In November 2021, the GPCR was effectively expanded again, this time aimed at the green housing loans segment. Eligible loans can be used for the purchase or construction of a new, energy-efficient residential building and modernization for the purpose of energy savings, in line with the EU Taxonomy.

This capital discount can be considered a green supporting factor (GSF): banks can deduct it from their Pillar II capital requirements. Its amount varies between 5 and 7 percent of each eligible gross exposure, depending on the degree of their 'greenness'. Loans and bonds which fulfill an even stricter criteria can obtain the higher discount. The total amount of the discounts is capped at 1.5 percent of the institutions' total risk weighted assets (RWAs). The program is voluntary[1] but participating banks must submit information on the loans and bonds included in the program.

GPCR has been very popular: in its first year, over 90 percent of all banks joined the program. Exposures covered by the program have been swelling steadily, from 87 billion HUF (~225 million EUR) in December 2020 to 539 billion HUF (~1.395 billion EUR) in October 2023. As a result of its success, the program's initial expiration year of 2025 was extended, and loans issued in 2025 might be eligible for capital discount for 5 consecutive years in up until 2030.

The remainder of the paper presents the data in the GPCR, contrasts the default probability of eligible vs. non-eligible loans, and calculates a 'fair' level of capital discount.

1.3. Data

The table used for the analysis was put together from several sources. First, we use the Credit Register of the Central Bank of Hungary's Credit Register (HITREG). This database contains granular, loan level information on all loans issued by Hungarian credit institutions in Hungary. It also covers basic information on the collateral and the debtor, which we joined to the loan-level table. The timeframe of the data stretches from the beginning of first quarter of 2020 until the end of the second quarter in 2023, on a quarterly basis. Second, we use the auxiliary reporting on the green preferential capital requirement program, which contains the same identifier that is used in the Credit Register. Third, we combine the credit data with the financial statements of the corresponding firms. Firm level financial variables were found in 73 percent of all loans. We use the previous year's balance sheet data to create our variables describing the financial state of firms. Finally, we use the data on the auction winners of Hungarian renewable feed-in tariff auctions (from 2012 to 2022) proxy for other renewable energy firms.

As a result of COVID-19 pandemic, loans (retail and business) issued before March 18th 2020 were eligible to participate in a repayment moratorium. The scheme was automatically applicable to all debtors subject to the legislation, and debtors preferring not to remain in the scheme had the option of opting out. A year later, many corporates (39 percent of the portfolio) still participated in the moratorium (Dancsik and Fellner, 2021), but at the beginning of 2023 the scheme ended. Naturally, defaults for loans in a moratorium is impossible, therefore, we focus on the loans where it is possible.

[1] This means that the debtor firm is most probably not aware of the fact that its financing bank obtains a capital requirement discount after its loan.

After the removal of loans issued before the start of the analysis, we have 2.3 million unique loan IDs[2] in the data. Since the average maturity of the loan portfolio is relatively short, we see between around 10 thousand IDs at the first reporting date, reaching 230 thousand by the beginning of 2022, when their numbers started to level off. Once loan IDs are aggregated to firm level, we see 569 thousand data points of credit performance. Out of that, we found financial statement figures for 396 thousand data points.

A loan contract was considered to be in default at a given date if it fulfilled the circumstances defined by the Capital Requirements Regulation (CRR) Art.[3] 178 in any of the three months *following* that date. This includes the case when the credit institution considers that the obligor is unlikely to pay its credit obligations; as well as when the obligor is more than 90 days past due on any material credit obligation.

At least 10 percent of the company's outstanding capital had to be in default to consider the firm as defaulted, in order to eliminate technical defaults, similarly to Banai et al. (2016). By introducing this threshold, we managed to exclude a substantial amount of technical defaults, as the share of default events drops from 1.2 percent to 0.7 percent.

Explanatory variables consist of macroeconomic data and credit and financial statement related firm-level data. Credit related variables include loan amount, value of collateral, time to maturity, contractual interest rate, if the loan is denominated in a foreign currency (as a dummy variable), as well as the purpose of the loan(s). Firm-level information are age, size, economic sector, and legal entity type. In addition, the county (corresponding to the NUTS-3 region[4]) where it was located, and whether more than 50 percent of its equity was owned by foreign entities, were also considered during the analysis. We create leverage[5], liquidity[6], ROA[7], EBITDA-to-equity[8] and sales-to-assets[9] indicators based on the firms' financial statements[10]. We choose these variables based on the related international (Altman, 1968; Neagu et al., 2023) and Hungarian credit risk literature (Banai at al. 2016; Burger 2022). Finally, the two main variables of interest are two dummy variables: whether the firm has any loans included in the preferential requirement program as a Renewable energy (RE) or Electro-mobility loan (EM), any time during the observed period.

Table 1: Summary statistics

[2] One firm can have several loan instruments, with one or with more financial institutions.

[3] Technically, the CRR Art 178 default definition was enhanced using two more columns: the column containing the Hungarian default definition, in line with the EU law, was also used. Next, default was also identified when the number of days past due over 90. The number of cases where there was a difference between the three default definitions was not material.

[4] NUTS stands for the Nomenclature of Territorial Units for Statistics, a georeferencing standard of the European Union.

[5] Defined as 1 – equity / total assets, capped at 1 and floored at zero.

[6] Defined as current assets divided by short term debt.

[7] Defined as after tax income as a percentage of total assets.

[8] Operating Profit plus depreciation, divided by total equity

[9] Defined as Revenues / total assets

[10] We winsorize these financial statement variables replacing the top and bottom 1 percent with the 99th and the 1st percentile respectively. In case of our liquidity measure, we winsorize below -10 and above 10.

Varible	Number of Observations	Mean	Standard Deviation	Minimum	25th percentile	Median	75th percentile	Maximum
Default event - unfiltered	568999	0.012	0.11	0	0	0	0	1
Default event - filtered	568999	0.007	0.086	0	0	0	0	1
Firm age (years)	568999	15.307	7.358	0.422	10.038	15.428	19.362	82.255
Foreign firm (dummy)	568999	0.02	0.139	0	0	0	0	1
Micro firm (dummy)	568999	0.632	0.482	0	0	1	1	1
Small firm (dummy)	568999	0.216	0.411	0	0	0	0	1
Medium firm (dummy)	568999	0.056	0.23	0	0	0	0	1
Large firm (dummy)	568999	0.088	0.283	0	0	0	0	1
Energy sector (dummy)	568999	0.006	0.077	0	0	0	0	1
Sales growth rate	395573	0.444	1.698	-1	-0.059	0.12	0.39	14.985
Leverage	407904	0.48	0.25	0	0.284	0.476	0.676	0.979
Liquidity	407904	2.86	2.675	0	1.128	1.83	3.474	10
EBITDA-to-Equity ratio	407904	0.381	0.439	-1.671	0.154	0.316	0.553	2.465
ROA (after tax)	407904	0.101	0.189	-1.502	0.018	0.069	0.171	0.744
Sales-to-Assets	407904	1.725	1.515	0	0.753	1.348	2.22	10.155
Elapsed loan term (longest)	568999	1.009	0.717	0	0.408	0.871	1.518	3.033
Remaining maturity (longest)	568999	3.47	2.972	-2.301	1.844	3.329	3.863	30
Logarithm of instrumentum size (HUF)	568999	2.761	2.112	-4.605	1.746	2.73	3.912	15.637
Logarithm of collateral value (HUF)	568999	-0.435	3.68	-4.605	-4.605	0.838	2.432	11.461
Collateral (dummy)	568999	0.296	0.457	0	0	0	1	1
HUF loan (dummy)	568999	0.977	0.149	0	1	1	1	1
Foreign currency loan (dummy)	568999	0.042	0.201	0	0	0	0	1
Floating rate (dummy)	568999	0.434	0.496	0	0	0	1	1
NHP loan (dummy)	568999	0.149	0.356	0	0	0	0	1
Szechenyi loan (dummy)	568999	0.429	0.495	0	0	0	1	1
Leasing loan (dummy)	568999	0.296	0.456	0	0	0	1	1
GPCR (dummy)	568999	0.021	0.143	0	0	0	0	1
GPCR Renewable energy (dummy)	568999	0.006	0.076	0	0	0	0	1
GPCR: Electromobility (dummy)	568999	0.015	0.122	0	0	0	0	1
All Renewable energy (dummy)	568999	0.011	0.103	0	0	0	0	1

Note: Observations are at the quarter – firm level, from the period of 2020-2023. First column contains the variable names, the following the number of observations containing the variable, the mean, the standard deviation, the minimum, the 25th percentile, the median, the 75th percentile and the maximum of the variable, respectively.

Table 1 shows that 0.6 percent of all observations (3312 pieces) were related to firms with Renewable Energy loan(s), very similar to the share of the Energy sector (0.6 percent) in the sample. There is an overlap between the two groups, 66 percent of the Energy sector firms have Renewable energy loans, but there are several firms with main activities other than Energy, but also have a Renewable energy loan. Firms with electromobility related loans had a 1.5 percent share of the observations (8558 pieces), considerably lower than the share of firms with leasing loans (29.6 percent). Subsidized loans take up a substantial part of the data, firms with government supported (Széchenyi Program) loans and small- and medium enterprises (SMEs) in the central bank's loan program (NHP) account for 42.9 and 14.9 percent respectively.

We compare our firms of interest (RE and EM firms) to relevant peer groups: all corporates in the sample ("whole sample"), renewable energy firms in ("GPCR: RE") and outside ("GPCR and other RE") the program, corporates in the energy sector (RE peers, "Energy sector") firms with GPCR loans financing electromobility ("GPCR: EM") and finally, firms with leasing loans (EM peers, "Leasing") in Table 2. Descriptives show that firms with leasing loans are similar to firms with EM loans, and these corporates do not differ too much from the overall sample. In contrast, energy firms' characteristics seem to deviate from the total sample, but are similar to firms with renewable energy loans. They tend to be younger, larger, and more likely to be foreign owned. In addition, they are more likely to have subsidized loans than other firms do.

Table 2: Summary statistics for green and non-green non disjoint group of observations

	Whole sample	GPCR: RE	GPCR and other RE	Energy sector	GPCR:EM	Leasing
Observations	568999	3312	6125	3427	8558	168157
Number of firms	88586	431	846	459	1241	26349
Default event - filtered	4200	4	15	6	23	1085
Quarterly default rate - filtered (%)	0.738	0.121	0.245	0.175	0.269	0.645
Quarterly default rate - unfiltered (%)	1.226	0.121	0.473	0.321	0.351	0.684
Yearly default rate - filtered (%)	2.92	0.482	0.976	0.698	1.071	2.556
Yearly default rate - unfiltered (%)	4.813	0.482	1.88	1.278	1.395	2.71
Median firm age	15.428	5.641	9.567	5.236	15.247	15.428
Mean firm age	15.307	8.823	11.634	7.599	14.871	15.127
Median leverage	0.476	0.885	0.746	0.882	0.5	0.452
Median liquidity indicator	1,83	1,003	1,218	0,949	1,708	1,955
Median EBITDA-equity ratio (%)	31,578	40,839	34,839	49,102	41,794	37,494
Median ROA (after tax) (%)	6,867	1,222	2,313	1,361	8,819	9,297
Loan backed by collateral (%)	29,604	49,819	41,812	39.481	17.901	16.624
Collateral value	38.722	155.748	131.877	123.939	86.853	38.019
Ratio of foreign firms (%)	1.976	11.685	7.118	11.38	0.736	1.666
Ratio of firms with floating rate loans (%)	43.402	25.604	32.082	27.896	46.004	40.887
Ratio of micro firms (%)	63.169	66.274	57.371	66.501	65.412	66.342
Ratio of small firms (%)	21.58	7.548	17.616	9.192	26.829	26.161

Ratio of medium firms (%)	5.601	10.628	12.751	9.775	5.971	5.487
Ratio of large firms (%)	8.765	14.402	11.184	12.985	1.017	1.361
Ratio of firms with subsidized loans - NHP (%)	14.886	63.829	51.167	56.084	15.272	24.721
Ratio of firms with subsidized loans - Szechenyi (%)	42.858	8.907	20.539	9.192	35.803	24.623
Ratio of firms with subsidized loans (%)	53.909	70.592	67.249	63.788	44.648	41.364

Note: Observations are at the quarter – firm level, from the period of 2020-2023. First column contains the statistic of a particular variable, the following columns contain that information across different, non disjoint sets. These groups are the whole sample, Renewable Energy firms in the Green Preferential Capital Requirement Program, Renewable Energy firms in and outside GPCR, firms in the energy sector, firms with electromobility loans and firms with leasing loans, respectively.

1.4. Methodology

We use two econometric techniques to evaluate the impact of green loans on default probability. Firstly, we estimate traditional logistic regressions. Secondly, we apply survival analysis methods by estimating extended Cox proportional hazard models. Logistic regressions have the advantage of being widely used and understood models, which are capable of estimating the effect of covariates and can calculate fitted default probabilities. In contrast, survival analysis methods' major strength is their ability to handle censored data (Stepanova & Thomas, 2000) and the term structure of risks. The methods are widespread in medical studies since the statistical power of these models is higher than those of logistic regression in many cases (van der Net, 2008), but are gaining popularity in financial modeling as well (Parker et al., 2002, Burger, 2011), especially in the credit risk area.

Logistic regression

By defining the default event for observation *i* as Y_i 1 for default and 0 for non-default and attribute k of observation i as $X_{i,k}$, we can model PD in the GLM framework as :

$$Prob(Y_i = 1|X_i) = E[Y_i|X_i]$$

$$logit(E[Y_i|X_i]) = \sum_k \beta_k \cdot X_{i,k}$$

$$Prob(Y_i = 1|X_i) = logit^{-1}(\alpha + \beta_{RE} \cdot RE_i + \beta_{EM} \cdot ME_i + \sum_k \beta_k \cdot X_{i,k})$$

The coefficients (betas) are obtained via maximum likelihood estimation, using the iteratively reweighted least squares method. The estimated coefficients' average marginal effects can be interpreted similarly to linear regressions and has been widely used to infer effects of explanatory variables in the credit literature as well (Billio et al., 2022).

Survival analysis

In survival analysis, the matter of interest is the time a performing loan ceases to perform (in our case, it defaults) after origination, which is a random variable, denoted by T. In the literature, the distribution of T is described by the survival function $S(t)$, which is the probability that a loan is performing up to time t,

$S(t) = Prob(t < T)$. Note that time in this case measures the time since loan origination, which is different for most firms, not calendar year. A possible way to model the distribution of T is introduce the hazard function of default risk, $h(t)$.

$$h(t) = \lim_{\Delta t \to 0} \frac{Prob(t \leq T < t + \Delta t \ \ |t \leq T)}{\Delta t}$$

The hazard function at time t is the probability that the loan defaults instantaneously, conditional on that it has survived to time t. It can be shown that the cumulative hazard function is closely related to the survival function in the following way: $\int_0^\infty h(t) = -\ln(S(t))$.

The proportional hazard Cox model (Cox, 1972) assesses the relationship between the covariates and the survival distribution using the hazard function. The model assumes that the hazard of firm i with the attributes $\boldsymbol{x_i}$ is proportional to a baseline hazard, denoted by $h_0(t)$. The extended version of the model allows for the covariates to change in the observation period, so $\boldsymbol{x_i}(t)$ becomes a function of time. The coefficients are maximum likelihood estimates.

$$h(t, \boldsymbol{x_i}(t)) = \exp(\beta' \boldsymbol{x_i}(t)) \cdot h_0(t)$$

Coefficients for each characteristics determine the hazard ratio ($\exp(\beta' \boldsymbol{x_i}(t))$). If the ratio is above (below) 1, the probability of default is higher (lower) for a firm with those characteristics than the baseline hazard ($h_0(t)$).

The main strength of survival analysis methods is that they can handle time varying risk . This is an important feature for credit risk analyses, since default risk in the first few years of the loan is substantially higher than later. Another advantage of this framework is that even if a loan originated before the observation period, or the loan did not expire during the observation period (the loan can default outside the observation window), it can still be included in the analysis. In case of early origination, the data is called left censored (or truncated), and in case of late maturity the data is called right-censored. Since we almost exclusively include loans originated in the observation period, right-censored data is a more relevant issue in our case.

Fair capital requirements

Capital requirements are risk based, namely, the Pillar I regulatory capital of the Basel framework is based on the Asymptotic Single Risk Factor (ASRF) model of Vasicek (2002). While the final implementation of capital requirements relies on a more complex methodology than the one of the ASRF model, the ASRF model serves as a good starting point to calculate the impact of PD on a theoretical capital requirement.[11] The assessment can provide the theoretical threshold for the minimal capital a bank needs to keep in order to limit their default probability to 0.01 percent or less in a year. This translates into sufficient capital to cover unexpected losses in 999 years out of 1000. We denote this as the 'fair' capital requirement. The ASRF formula is the following:

[11] There are multiple differences between this calculation and the current regulation. Firstly, only Pillar I requirements are based on the ASRF, while the GPCR is implemented in Pillar II. Secondly, there are multiple approaches banks can use to calculate their minimum required capital, and it is only the Internal Rating Based approach related to the ASRF. Banks using the standardized approach are calculating capital based on predefined values.

$$Fair\ Cap\ Req = LGD \cdot \left(\Phi\left(\sqrt{\frac{1}{1-R}} \cdot \Phi^{-1}(PD) + \sqrt{\frac{R}{1-R}} \cdot \Phi^{-1}(0.999) \right) - PD \right) \cdot M\_adj$$

whereby

- $\Phi()$ is the normal cumulative distribution function
- $M_{adj} = \frac{(1 + (M - 2.5) * b)}{(1 - 1.5 * b)}$ and $b = (0.11852 - 0.05478 * log(PD))^2$
- The correlation coefficient, according to the Basel regulation, $R = 0.12 \cdot w + 0.24 \cdot (1 - w)$, where $w = \frac{(1 - exp(-50 \cdot PD))}{(1 - exp(-50))}$.
- LGD stands for the loss given default value for the relevant bank asset portfolio.

We use the ASRF formula as a function of PD to measure the fair capital impact. We use the following regulatory values to the formula: (Loss Given Default as 45 percent, maturity of 2.5 years and correlation coefficients as a function of PD).

1.5. Results

1.5.1. Default probabilities

We estimate logit models to examine green firm's characteristics in more detail. The dependent variable is whether the firm had any RE loan during the observed period. The results (Table 3, left panel) verify the conclusion of descriptive statistics, while also show that RE firms borrow more than other corporates; and that those loans are less likely to be floating rate loans and more likely fixed rate ones. Higher leverage, a classical credit risk factor is correlated with firms being included in GPCR as RE. Higher sales growth and EBITDA-to-Equity are associated with RE firms, while profitability measures based on asset intensity are lower compared to others. Regarding firms with EM loans (Table 3, right panel), the regression estimates suggest that they significantly differ from other corporates. Lower liquidity and sales relative to assets and higher EBITDA to Equity ratio is associated with EM firms. Apart from these differences, others have less economic significance (currency of the loan(s), smaller instrument size, less likely to have subsidized loans, generally smaller firms).

Table 3: Logit regressions on Renewable energy generation and Electromobility firms

	Dependent variable:					
	GPCR RE			GPCR EM		
	(1)	(2)	(3)	(4)	(5)	(6)
Firm age (years)	-0.049***	-0.024***	-0.015***	-0.004**	-0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
Small firm	-0.477***	-0.447***	-0.329**	2.411***	1.349***	0.791***
	(0.107)	(0.138)	(0.141)	(0.111)	(0.116)	(0.119)
Medium firm	0.839***	0.251*	-0.214	2.318***	1.281***	0.639***
	(0.112)	(0.147)	(0.148)	(0.118)	(0.122)	(0.124)
Micro firm	-0.060	-0.305***	0.342***	2.150***	1.098***	0.842***
	(0.076)	(0.115)	(0.121)	(0.110)	(0.115)	(0.119)
Firm size missing	-0.561**	-0.332	-0.163	1.986***	1.220***	1.037***

	(0.246)	(0.299)	(0.310)	(0.165)	(0.171)	(0.174)
Foreign firm (dummy)	1.182***	1.002***	0.988***	-0.746***	-0.777***	-0.770***
	(0.121)	(0.127)	(0.127)	(0.128)	(0.130)	(0.131)
Sales growth rate		0.045***	0.024**		0.025***	0.011
		(0.010)	(0.011)		(0.007)	(0.007)
Liquidity		-0.025**	-0.001		-0.019***	-0.020***
		(0.011)	(0.012)		(0.006)	(0.006)
Leverage		0.641***	0.221*		0.054	0.019
		(0.115)	(0.120)		(0.074)	(0.077)
ROA (after tax)		-0.405**	-0.600**		0.245***	-0.106
		(0.201)	(0.244)		(0.094)	(0.095)
EBITDA to Equity ratio		0.292***	0.297***		0.505***	0.326***
		(0.049)	(0.051)		(0.035)	(0.037)
Sales to Assets		-2.569***	-1.700***		-0.113***	-0.065***
		(0.100)	(0.091)		(0.010)	(0.010)
HUF loan (dummy)			0.561***			1.175***
			(0.209)			(0.266)
Foreign currency loan (dummy)			0.501***			-0.569***
			(0.163)			(0.089)
Logarithm of instrumentum size (HUF)			0.383***			0.188***
			(0.023)			(0.012)
Leasing (dummy)			-1.711***			1.987***
			(0.157)			(0.034)
Logarithm of collateral value (HUF)			0.019**			0.049***
			(0.008)			(0.006)
Floating rate (dummy)			-0.323***			0.086***
			(0.082)			(0.028)
Subsidized loan - NHP (dummy)			0.753***			-0.554***
			(0.085)			(0.037)
Subsidized loan - Szechenyi (dummy)			-0.592***			-0.028
			(0.096)			(0.030)
Economic sector control	Yes	Yes	Yes	Yes	Yes	Yes
Firm legal entity control	Yes	Yes	Yes	Yes	Yes	Yes
Firm age missing	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	No	No	No	No	No	No

Observations	568,999	395,573	395,573	568,999	395,573	395,573
Log Likelihood	-8,808.012	-5,069.045	-4,481.824	-42,980.430	-31,468.710	-28,466.130
Akaike Inf. Crit.	17,716.020	10,250.090	9,091.647	86,060.850	63,049.430	57,060.270

*Note: The table presents the results of green firms in the GPCR determinant model. The left part of the table shows coefficient estimates for renewable energy firms, the right part for firms with Electromobility loans. For each dependent variable, the first model uses basic firm information, the second adds financial data on the firm, the third contains credit information as well. For each variable (first column), the estimated coefficients and the standard error (in parentheses) are shown, as well as their p-values denoted by stars (**p<0.1; **p<0.05; ***p<0.01*).*

The observed default rates for RE, EM and for other firms (see Table 2) show that, when not controlling for other factors, green firms' are less risky. However, there are several covariates that increase risk, and our goal is to disentangle the effects of these known risk factors from the effect of RE and EM. By introducing these covariates into the employed models, we estimate the additional information of these green loans on corporate PD.

The results of the estimated logistic regressions are presented by Table 4. The coefficients of firms having RE or EM loans as well as firms having leasing loan are presented in full detail. We grouped the rest of controlling covariates into the four broad categories previously described: (1) macroenvironment, (2) basic firm data, (3) credit related and (4) financial statement based information. Since economic sectors play a crucial role in determining the additional information value of RE loans, we included it in a separate row, and analyze it in more detail. An additional category is the introduced missing flag dummies for numerical variables[12].

We estimated several models to obtain more robust results and to isolate the effect of RE and EM on corporate default risk. Model (1) describes the effect of RE and EM on PD without controlling for any other covariate. In Model (2) we control for the macroeconomic environment (via quarterly fixed effects) and for basic firm data (age, size etc.). In Model (3) we additionally control for the economic activity of the firm using NACE level 1 sector. We introduce control variables in Model (4), where credit and leasing-related covariates are also included. Finally, we introduce the credit risk relevant variables based on the corporate's financial statement (leverage, liquidity etc.) in Model (5). Via this step-by-step approach we can detect at which point the lower risk of RE firms disappears (if it does).

Table 4: Logistic regression estimates to determine the impact of Renewable Energy operations and Electromobility loans on corporates' probability of default.

	(1)	(2)	(3)	(4)	(5)
GPCR RE	-1.826***	-2.152***	-1.393**	-1.504***	-1.569**
	(0.498)	(0.501)	(0.566)	(0.562)	(0.652)
GPCR EM	-1.027***	-1.104***	-1.087***	-0.953***	-0.790***

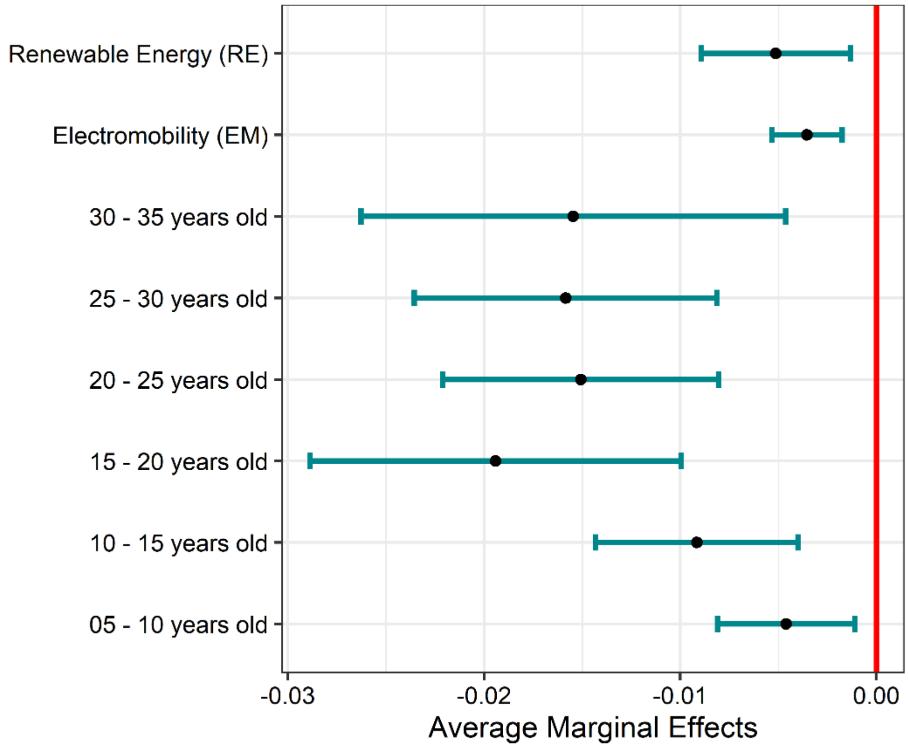
[12] Our only numerical variable with missing values is remaining maturity. We imputed the mean of non-missing values and introduced a new dummy variable to control for biases. In case of categorical variables, we introduced a missing category when it was necessary.

	(0.209)	(0.210)	(0.210)	(0.211)	(0.239)
Leasing dummy				-0.240***	-0.093*
				(0.044)	(0.054)
Sales growth rate					0.012
					(0.012)
Liquidity					-0.027***
					(0.010)
Leverage					0.832***
					(0.093)
ROA (after tax)					-1.336***
					(0.102)
EBITDA to Equity ratio					-0.128***
					(0.046)
Sales to Assets					-0.043***
					(0.016)
Credit related controls	No	No	No	Yes	Yes
Economic sector control	No	No	Yes	Yes	Yes
Firm related controls	No	Yes	Yes	Yes	Yes
Missing data control	No	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes
Observations	568,999	568,999	568,999	568,999	395,573
Akaike Inf. Crit.	49,547.500	48,634.960	48,494.140	47,758.760	29,585.930
AUROC	0.5072	0.6395	0.6482	0.6878	0.7033

*Note: Credit related controls include longest elapsed loan term and remaining maturity; existing floating rate loan indication, logarithmized collateral value, logarithmized loan amount, loan denominated in foreign exchange indication, loan denominated in HUF indication and subsidized loan indications (NHP and Szechenyi). Firm related controls are age (categories with 5-year buckets), size (micro, small, medium or not SME), legal entity type and whether it is a foreign entity. Changes in the macroeconomic environment are controlled by the quarter fixed effects. For each variable (first column), the estimated coefficients and the standard error (in parentheses) are shown, as well as their p-values denoted by stars (**p<0.1; **p<0.05; ***p<0.01*).*

The coefficients of RE suggest that RE decreases the probability of default for firms. Coefficient estimates are in the range of -1.39 to -2.15. These coefficients would imply an average marginal effect of somewhere between 55 and 65 bps decrease in quarterly PD for firms with RE loans. This is a large effect, as average quarterly default rate was 74 bps. Yearly PD impacts are in the range of 2.19 and 2.57 percentage points compared to the 2.92 percent average PD. Across all the estimated models, the coefficient is statistically significant. Even in Model (5), where all variables describing the financial situation of the firm are controlled for, the effect of RE is highly significant. It is important to emphasize that RE effect remains significant even after controlling for economic activity of firms. This implies that RE indicates lower PD even for firms in the energy sector, where default rates were low (see Table A1). The discriminant power of Model (5) is sufficient based on the 70.3 percent value for the area under the ROC curve (AUROC) measure.

Figure 1: Estimated average marginal effects of green and age groups in Model (5)



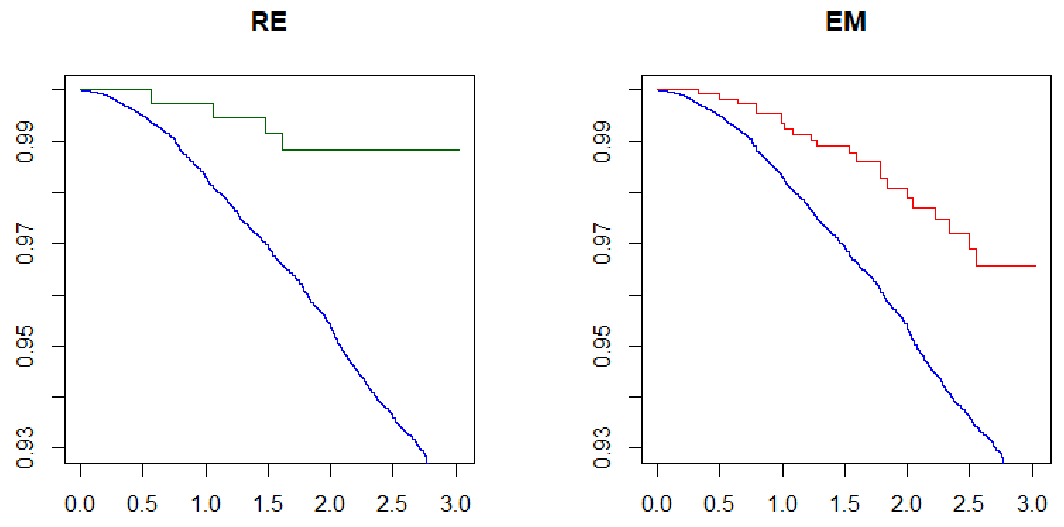
Note: The reference group is 0-5 years firms and not SME corporations. Confidence intervals are based on the 95th percentiles.

Average marginal effects are large in most models since RE firms are younger and relatively smaller than other firms, but empirically less risky. Greenness seems to compensate for these other credit risk factors. Figure 1 illustrates this mechanism using the results of the baseline logit Model (5). Young firms are substantially riskier, but RE (51 bps) compensate the risk difference between less than 5 year old and 5-10 year old firms (46 bps).

Regarding EM, our results show that the additional information value of EM (all else equal) decreases probability of default. All our estimated models suggest that this effect is statistically significant (even at a 1 percent level). The coefficient estimates range from -0.79 to -1.10 which imply that it is a stable effect. The estimated impact on quarterly PD ranges from 40 to 49 bps (1.59 to 1.93 percentage points yearly). If we control for firms, which are expected to be similar via the leasing loan indicator, the results don't change, EM remains significant (Model (4)-(5)). Whether the credit information or financial state of firms is included does not affect the estimates either. Similarly to RE, if only RE and EM information are part of the model, the coefficients are significantly negative.

Before analyzing the results of the Cox model, the proportional hazard assumption's validity is addressed. Figure 2 shows that the probability of survival for both RE and EM is constantly higher than for other firms. This is in line with the results of logistic regressions, especially Model (1). Additionally, it implies that the proportional hazard assumption is not falsified, since the groups' survival functions do not cross.

Figure 2: Kaplan-Meier survival probabilities for RE, EM and other firms



Note: RE firms' survival probabilities are denoted by green on the left panel, EM firms' survival probabilities are denoted by red on the right panel. Relative time since loan origination is measured in years in the x-axis.

The survival analysis models are designed in a similar manner to the logistic regression models: we stick to the grouping of the covariates and introduce them in the same order as previously. The results are shown in Table 5. The main difference compared to the logistic regressions are that the extended proportional Cox model captures the varying risk after origination, and that healing of firms is not allowed. Moreover, only hazard *ratios* are estimated, hence, the direct effect of explanatory variables on the absolute hazard is not captured.

Table 5: Survival analysis results to determine the impact of Renewable Energy operations and Electro-mobility loans on corporates' time to default

	(1)	(2)	(3)	(4)	(5)
GPCR RE	-1.637***	-1.929***	-0.985*	-1.153**	-1.319**
	(0.500)	(0.501)	(0.576)	(0.574)	(0.665)
GPCR EM	-0.871***	-0.904***	-0.895***	-0.854***	-0.709***
	(0.214)	(0.214)	(0.214)	(0.215)	(0.226)
Leasing dummy				-0.186***	-0.116**
				(0.048)	(0.055)
Sales growth rate					0.040***
					(0.010)
Liquidity					-0.011
					(0.010)
Leverage					0.923***
					(0.101)
ROA (after tax)					-0.670***
					(0.129)

EBITDA to Equity ratio					-0.133***
					(0.050)
Sales to Assets					0.048***
					(0.014)
Credit related controls	No	No	No	Yes	Yes
Economic sector control	No	No	Yes	Yes	Yes
Firm related controls	No	Yes	Yes	Yes	Yes
Missing data control	No	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes
Observations	562,371	473,885	473,885	473,885	350,368
R2	0.0001	0.002	0.002	0.003	0.004
Max. Possible R2	0.130	0.139	0.139	0.139	0.136
Wald Test	27.270*** (df = 2)	904.330*** (df = 50)	1,037.100*** (df = 68)	1,431.340*** (df = 76)	1,286.440*** (df = 82)
LR Test	42.397*** (df = 2)	903.201*** (df = 50)	1,033.422*** (df = 68)	1,460.003*** (df = 76)	1,299.147*** (df = 82)
Score (Logrank) Test	30.957*** (df = 2)	950.428*** (df = 50)	1,090.505*** (df = 68)	1,497.282*** (df = 76)	1,337.464*** (df = 82)

*Note: Credit-related controls include existing floating rate loan flag, logarithmized collateral value, logarithmized loan amount, flag for loan denominated in foreign exchange, flags for the loan denominated in HUF and for subsidized loan (NHP and Szechenyi). Firm-related controls are age (categories with 5-year buckets), size (micro, small, medium or not SME), legal entity type, NUTS-3 firm headquarters location and whether it is a majority foreign-owned entity. Changes in the macroeconomic environment are controlled by the quarterly fixed effects. For each variable (first column), the estimated coefficients and the standard error (in parentheses) are shown, as well as their p-values denoted by stars (**p<0.1; **p<0.05; ***p<0.01*).*

The results are in line with the estimates of the logistic regressions both for RE and EM. Coefficients of RE are significant in all cases. The range of estimates is between -1.9 and -0.98. These coefficients correspond to relative hazard ratios of 14.5 and 37.5 percent respectively, while our most detailed model (5) implies a 26.7 percent hazard ratio for RE. This means that the RE flag decreases hazard compared to similar firms by a value between 62.5 and 85.5 percent – as described by the different models. Model (5) suggests 73.3 percent decrease in risk.

The coefficients of EM are significant and more robust than the ones of the logistic regression results. The estimates are between -0.9 and -0.71, which imply hazard ratios within the range of 40.4 and 49.2 percent. Corresponding to a decline of hazard in the range of 59.8 to 50.4 percent. The hazard ratio estimate of Model (5) is 49.2 percent.

1.5.2. Default probabilities using the broader default definition

One main limitation of the analysis is the low number of green energy firm defaults. To counterbalance, we assess the robustness of our results by increasing the number of green defaulted firms in two ways. Firstly, we estimate the same logistic regression models using the unfiltered default definition of firms. In this case if any loan of the firm in the observed period defaults, we flag the firm as default (compared to the filtered definition, whereby at least 10 percent of the loan exposures has to be in default) . This potentially introduces several technical defaults into our sample. At the same time, some of these additional new default observations may indicate fundamental solvency or liquidity problems. Secondly, we include an additional data source to the analysis on the winners of renewable energy auctions supported by the government from 2012 to 2022. This way the number of green renewable energy observation in the sample almost doubles (to 6,115). This part of the analysis confirms that renewable energy firms are less risky overall, not only those that are included in the capital requirement program.

Table A2 and A3 illustrate the results of the new two sets of logistic regressions, while Table A4 presents the estimates of the extended Cox model with more green energy firms outside the GPCR. The results of the three (filtered and unfiltered default as response variables, and all RE used for identification) full logit models (5) are summarized in Table 6. The more inclusive definition of RE firms (All RE) has an even more significant effect due to the lower standard errors of the estimates. The estimated economic impact is a bit lower than in case of the 'GPCR only RE' variable. The estimated coefficients are relatively stable across the presented models. This suggests that RE loans in the program are not special, other RE firms on our sample exhibit lower default risk as well. Overall, our results are robust and not depend on default definitions or RE identification. The results of the survival analysis support these findings too, see Appendix Table A4.

Table 6: Logistic regression estimates of the extended models with filtered, unfiltered and all RE

	(Filt 5)	(Unfilt 5)	(GPCR and other RE 5)
GPCR and other RE			-0.900***
			(0.336)
GPCR RE	-1.569**	-1.588**	
	(0.652)	(0.628)	
GPCR EM	-0.790***	-0.491**	-0.792***
	(0.239)	(0.207)	(0.239)
Leasing dummy	-0.093*	-0.244***	-0.092*
	(0.054)	(0.051)	(0.054)
Sales growth rate	0.012	0.024***	0.012
	(0.012)	(0.009)	(0.012)
Liquidity	-0.027***	-0.025***	-0.027***
	(0.010)	(0.008)	(0.010)
Leverage	0.832***	0.667***	0.834***
	(0.093)	(0.078)	(0.093)
ROA (after tax)	-1.336***	-0.956***	-1.334***
	(0.102)	(0.084)	(0.102)
EBITDA to Equity ratio	-0.128***	-0.162***	-0.129***
	(0.046)	(0.041)	(0.046)
Sales to Assets	-0.043***	-0.095***	-0.043***

	(0.016)	(0.014)	(0.016)
Credit related controls	Yes	Yes	Yes
Economic sector control	Yes	Yes	Yes
Firm related controls	Yes	Yes	Yes
Missing data control	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	568,999	568,999	395,573
Akaike Inf. Crit.	63,974.830	63,947.150	36,145.360

*Notes: The 'all RE' variable includes the winners of renewable energy auctions, besides the firms in the RE:GPCR program. Unfiltered default: any loan default implies firm default[13]. Credit-related controls include longest elapsed loan term and remaining maturity; a flag if any of the existing loans was floating rate loan, the logarithm of the collateral value, the logarithm of the (authorized) loan amount, a flag if the loan is denominated in foreign currency, flag if the loan denominated in HUF[14] and flags if the loan was subsidized (NHP and Széchenyi). Firm related controls are age (categories with 5-year buckets), size (micro, small, medium or not SME), legal entity type, county of firm's location (NUTS-3 region) and whether it is a foreign entity. Changes in the macroeconomic environment are controlled by the quarterly fixed effects. For each variable (first column), the estimated coefficients and the standard error (in parentheses) are shown, as well as their p-values denoted by stars (*p<0.1; **p<0.05; ***p<0.01).*

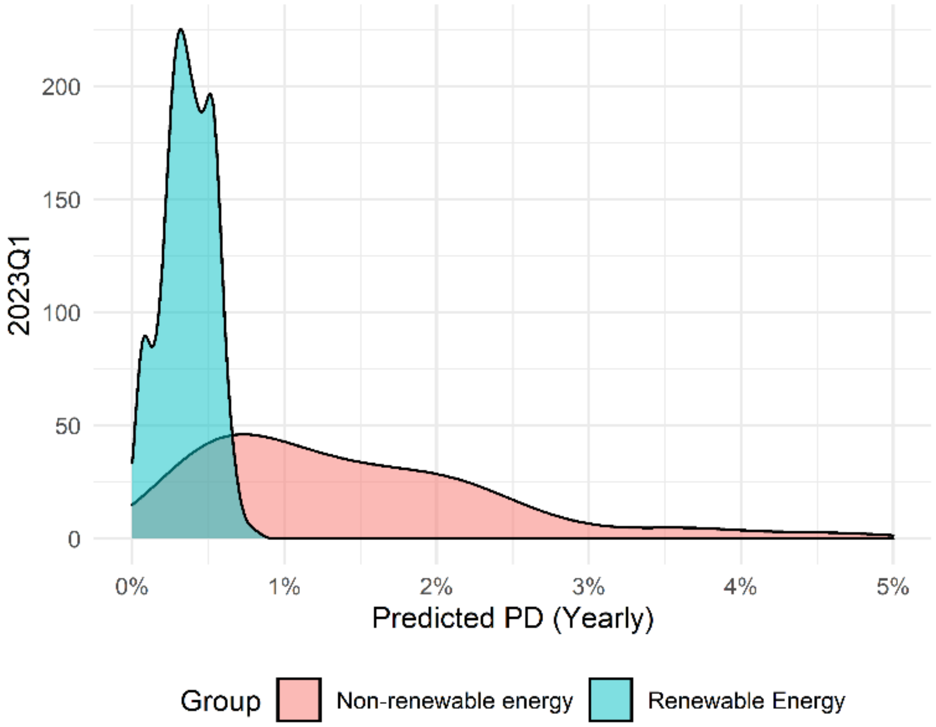
To assess whether sustainable loans are less risky overall, we compare the distribution of their estimated PDs to the PDs of their peer groups. We define energy firms without renewable energy loans and corporates with leasing loans as the control group of RE and EM respectively. We predict the default probabilities of the portfolios with Model (5), using the values from the last quarter in the sample. Results are shown by Figure 3 for energy firms and Figure 4 for firms with leasing contracts. The distributions of estimated PDs show that RE firms are less risky in general, and the PD of firms is more centered around their mean than the PDs of other energy firms. The case for EM loans is similar, but the differences are less striking. [15] These results are in line with the descriptive statistics of default regarding these groups, shown previously.

Figure 3: Predicted PD for energy firms in the first quarter of 2023

[13] The filtered default definition requires that at least 10 percent of a firm's loan exposure has to be in default.

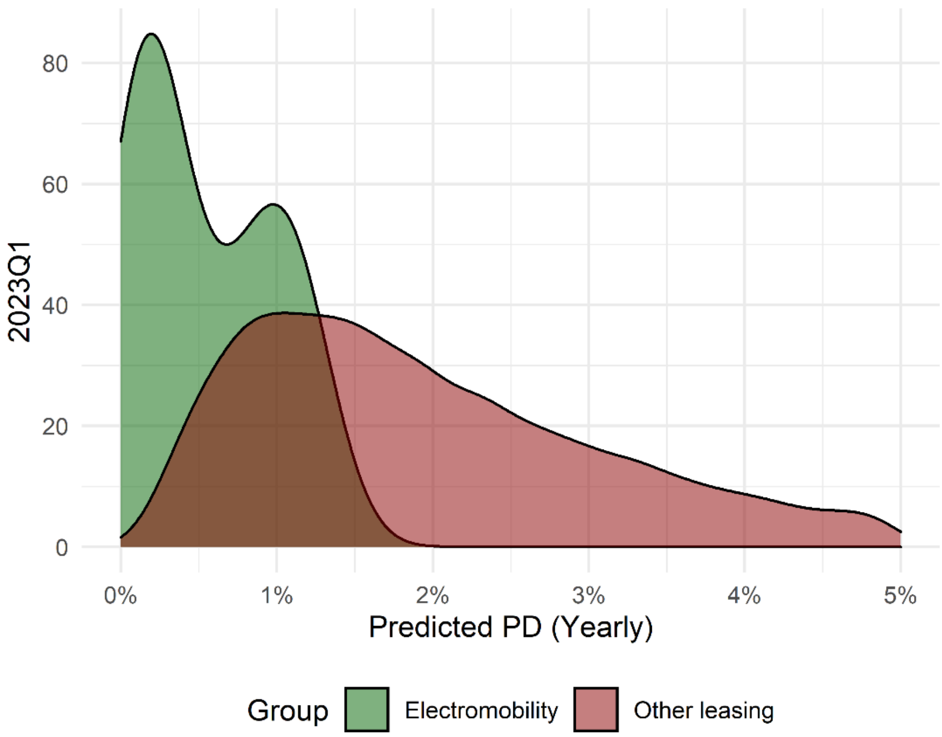
[14] While most firms have HUF denominated loans only (96 percent), around 2-2 percent of them carry FX-denominated loans only or have both.

[15] Note that Model (5) used for prediction requires financial statement information. This means that for the observations with missing data it cannot estimate PD. Using Model (4) instead, however, does not impact our conclusions.



Note: Estimations are based on Model (5) for RE firms and other energy firms in the last quarter of the sample (2023 Q1). Default probabilities were converted to yearly values.

Figure 4: Predicted PD for electromobility and other firms with leasing loans in the first quarter of 2023



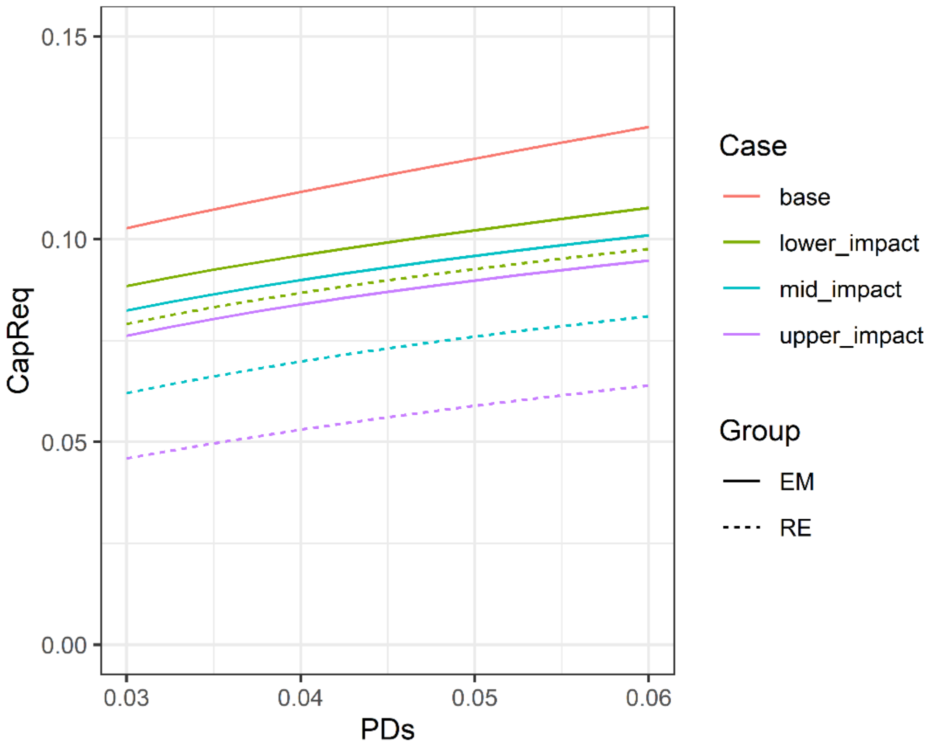
Note: Estimations are based on Model (5) for EM firms and firms with other leasing loans in the last quarter of the sample (2023 Q1). Default probabilities were converted to yearly values.

1.5.3. Implications for capital requirement calculation

Finally, we look at the capital requirement implications of the obtained estimates. Using the results of the logit Model (5), we calculate a range of possible Fair Capital Requirement values, both point estimates and their 2 standard deviation confidence intervals. We calibrate the capital impact both for RE and EM. Results of the capital calibrations are shown in Figure 5.

The broad range of possible impacts on fair capital requirement is between 1.4 and 3.3 percentage points for EM and between 2.4 and 6.4 for RE. With the most plausible value of 5 percent as a through the cycle PD for corporates, the average marginal effects would imply a fair capital impact between 1.8 and 3 percentage points for EM (2.4 for the point estimate), and between 2.7 and 6.1 for RE (4.4 for the point estimate).

Figure 5: Fair capital requirements for the corporate segment as a function of PD

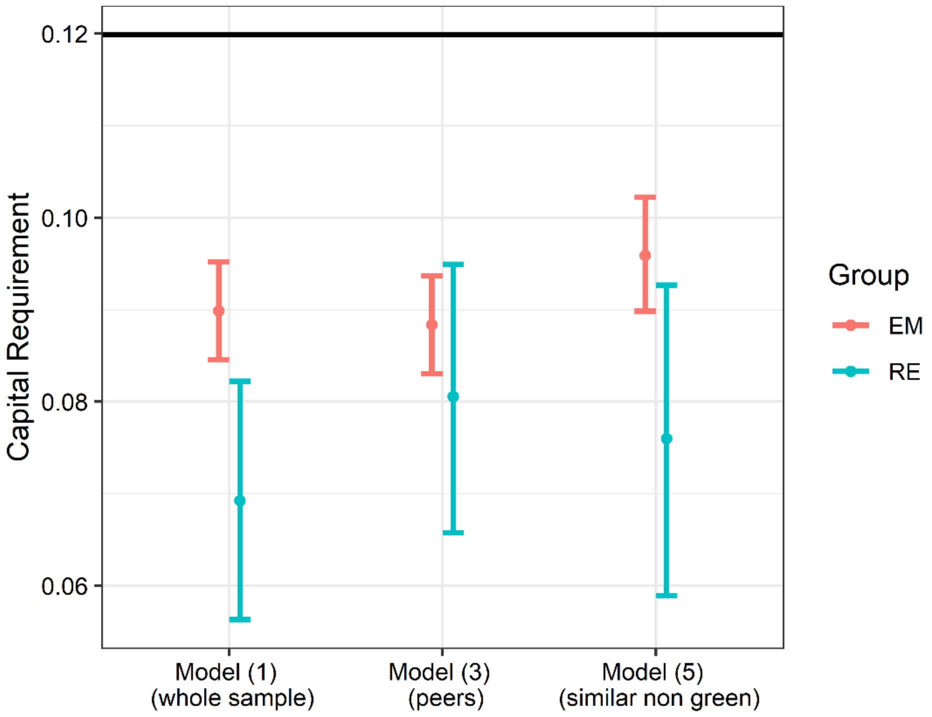


Note: Results based on the range of logit Model (5)'s odds ratios, a lower bound of 40.0 and upper bound of 10.8 percent for RE firms and a lower bound of 57.6 and upper bound of 35.7 percent for EM firms. Dotted line represents fair capital requirements for RE, solid lines for EM.

It is not trivial that capital impact should be based on the difference between green and similar but non-green firms, as in Model (5). The majority of the banks use the standardized approach (SA) to calculate capital in Hungary and in most emerging economies. These approaches also aim to be risk sensitive but are not as accurate as IRB approach. For instance, few distinctions are made for SME corporates in the SA approach.

Therefore we calibrate capital impact using our less informed logistic PD models, Model (1) and (3), which is more similar to the SA-approach. Model (1) compares capital impact based on the PD difference of green firms to the whole sample, while Model (3) to the peers in the given sector and similar basic firm characteristics. Results of the calibration, using 5 percent PD, are shown in Figure 6. These suggest that there are no striking differences among the cases. Capital impacts based on risk difference to the whole sample are larger for both RE and EM (5.0 and 3.0 percentage points respectively), while the effects based on their peers are smaller for RE (3.9) but very similar for EM (2.4). Uncertainties around our calibrations are similar to those presented before, somewhat smaller for RE.

Figure 6: Fair capital requirements for the corporate segment for Model (1), (3) and (5)



Note: Results based on the range of logit Model (1), (3) and (5)'s odds ratios for RE and EM, and their respective confidence intervals. Capital requirements are based on the PD difference between green firms and the whole sample (Model (1)), peer firms (Model (3)) and similar non-green firms (Model (6)). PD is set at 5 percent in all cases. Black line represents the baseline capital requirement.

These results show that for energy loans a 5 percent capital deduction in the GPCR might be justifiable solely by the risk differential between green and non-green assets. Half of this discount is validated even for lower bound impacts. We estimate that the different risk profiles could explain around half of the discounts for EM loans. At the same time, 7 percent discount does not seem to be justifiable by our calculations. Note, that these estimates are based entirely on historical data. Transition risks are expected to rise in case of several climate scenarios (NGFS 2023) which can impact the risk differentials of sustainable and non-sustainable loans even further. Conversely, in the upcoming years, this risk difference might decrease for other reasons. Additionally, since exposures are eligible to discount only for 5 consecutive years, portfolios with longer maturities have effectively lower discounts on average during their term.

1.5.4. Limitations

The main limitation of our analysis is the short time frame of our sample which is set by the duration of the program. Additionally, the relative share of green loans and firms in our sample is low, and the number of defaulted observations is even lower (mainly because low risk of green firms). This issue is more pronounced for RE firms. While we keep monitoring the robustness of our results, there is a sense of urgency to inform international policy discussion on the topic. Investigating other periods and gathering evidence from other economies is essential to assess the lower risk levels of sustainable activities in a robust manner.

1.6. Conclusion

Capital requirements are risk based. Hence one needs to investigate the risk profile of green loans to assess the adequacy of their preferential treatment in the microprudential framework. In this paper, we analyze the credit risk performance of firms with renewable energy and electromobility loans in a unique green preferential capital requirement program from Hungary. Banks participating in the program can get preferential capital rates for eligible green loans. We employ logistic regressions and extended Cox proportional hazard models to assess probability of default for included green firms.

We find that renewable energy firms participating in the program are more indebted and generally younger firms. Their equity and sales-based profitability metrics are higher than others', even compared to their sector peers. We find that firms with electromobility loans have similar characteristics to other firms with leasing loans.

We provide first evidence that loans in a green capital program have empirically lower default rates. It suggests that renewable energy firms compensate for the additional default risk implied by their young age. Additionally, we show that even after controlling for all relevant risk factors and firm characteristics, firms with renewable energy and electromobility loans still exhibit lower probability of default values. Our results are robust for estimation methodologies, identification of firm sustainability and to default definitions as well.

Using a simplified version of the capital requirement calculation formula (via an asymptotic single risk factor model), we show that while the capital discount for green loans in the framework is generous, at least half of this discount is validated by our results. Some of our estimates for renewable energy justify the entire discount.

Our results are relevant for supervisors investigating appropriate green tools to introduce in capital requirements. These findings can also inform policy makers on the expected cost of risk on green credit guarantee schemes. While we think these findings can provide valuable information for international discussion on sustainable finance policy tools, we are also aware of the limitation of our analysis.

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1.8. Appendix

Table A1: Descriptive statistics across NACE-Sectors

Sector	Number of Observations	Ratio of the sector	Ratio of renewable energy in sector (%)	Ratio of electromobility in sector (%)	Green ratio (%)	Default rate - filtered (%)	Defaulted observations - filtered
Agriculture, forestry, fishing (A)	26440	4,647	0,148	0,102	0,484	0,923	244
Mining and quarrying (B)	508	0,089	2,165	0	2,165	0,984	5
Manufacturing (C)	63203	11,108	0,087	0,454	1,193	0,734	464
Electricity, gas, steam and air conditioning supply (D)	3427	0,602	66,385	0,146	66,735	0,175	6
Water supply, sewerage collection and treatment, waste management and remediation activities (E)	2155	0,379	0	0,418	1,717	0,557	12
Construction industry (f)	70492	12,389	0,203	0,607	1,691	1,156	815
Trade and repair of vehicles (G)	133118	23,395	0,05	0,752	1,769	0,687	915
Transportation and storage (H)	26274	4,618	0,065	0,575	1,195	0,814	214
Accommodation and food service activities (I)	19898	3,497	0,146	0,553	1,407	0,689	137
Information and	15784	2,774	0	1,66	3,282	0,836	132

communication (J)							
Financial and insurance activities (K)	2642	0,464	0,643	1,325	2,574	0,454	12
Real estate activities (L)	21567	3,79	0,366	0,779	1,85	0,714	154
Professional, scientific and technical activities (M)	39798	6,994	0,168	1,168	2,239	0,691	275
Administrative and support service activities (N)	19872	3,492	0,05	1,178	2,999	1,001	199
Education (P)	2787	0,49	0	0,287	1,148	0,825	23
Human health and social work activities (Q)	10811	1,9	0,12	0,98	1,794	0,351	38
Arts, entertainment and recreation (R)	3648	0,641	0	0,74	1,48	0,877	32
Other services (S)	3858	0,678	0	1,063	2,1	0,674	26
Other sectors	195	0,034	0	0	0	1,026	2
Missing sectoral inforamtion	102522	18,018	0,479	0,902	1,614	0,483	495

Note: Observations are at the quarter – firm level, from the period of 2020-2023. First column contains the NACE sector names.

Table A2: Logistic regression estimates using unfiltered default event as response variable

	Default event - unfiltered				
	(1)	(2)	(3)	(4)	(5)
RE	-2.340***	-2.127***	-2.061***	-1.535***	-1.588**
	(0.498)	(0.501)	(0.537)	(0.536)	(0.628)
EM	-1.274***	-1.029***	-1.018***	-0.708***	-0.491**
	(0.183)	(0.184)	(0.184)	(0.185)	(0.207)
Leasing dummy				-0.340***	-0.244***

				(0.041)	(0.051)
Sales growth rate					0.024***
					(0.009)
Liquidity					- 0.025***
					(0.008)
Leverage					0.667***
					(0.078)
ROA (after tax)					- 0.956***
					(0.084)
EBITDA to Equity ratio					- 0.162***
					(0.041)
Sales to Assets					- 0.095***
					(0.014)
Credit related controls	No	No	No	Yes	Yes
Economic sector control	No	No	Yes	Yes	Yes
Firm related controls	No	Yes	Yes	Yes	Yes
Missing data control	No	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes
Observations	568,999	568,999	568,999	568,999	395,573
Akaike Inf. Crit.	75,131.100	69,165.070	69,052.750	63,974.830	36,145.3 6

*Note: Any defaulted loan of a company imply that the firm is in default. Credit related controls include longest elapsed loan term and remaining maturity; existing floating rate loan indication, logarithmized collateral value, logarithmized loan amount, loan denominated in foreign exchange indication, loan denominated in HUF indication and subsidized loan indications (NHP and Szechenyi). Firm related controls are age (categories with 5-year buckets), size (micro, small, medium or not SME), legal entity type, county of firm's location and whether it is a foreign entity. Changes in the macroeconomic environment are controlled by the quarter fixed effects. For each variable (first column), the estimated coefficients and the standard error (in parentheses) are shown, as well as their p-values denoted by stars (*p<0.1; **p<0.05; ***p<0.01).*

Table A3: Logistic regression estimates using renewable energy firms outside the GPCR too

	(1)	(2)	(3)	(4)	(5)
All RE	-1.121***	-1.339***	-0.787***	-0.890***	-0.900***
	(0.259)	(0.260)	(0.301)	(0.301)	(0.336)
EM	-1.029***	-1.106***	-1.087***	-0.955***	-0.792***

	(0.209)	(0.210)	(0.210)	(0.211)	(0.239)
Leasing dummy				-0.240***	-0.092*
				(0.044)	(0.054)
Sales growth rate					0.012
					(0.012)
Liquidity					-0.027***
					(0.010)
Leverage					0.834***
					(0.093)
ROA (after tax)					-1.334***
					(0.102)
EBITDA to Equity ratio					-0.129***
					(0.046)
Sales to Assets					-0.043***
					(0.016)
Credit related controls	No	No	No	Yes	Yes
Economic sector control	No	No	Yes	Yes	Yes
Firm related controls	No	Yes	Yes	Yes	Yes
Missing data control	No	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes
Observations	568,999	568,999	568,999	568,999	395,573
Akaike Inf. Crit.	49,546.330	48,634.440	48,493.830	47,757.550	29,584.800

*Note: Winners of renewable energy auctions are included too in the GPCR and other RE variable. Credit related controls include longest elapsed loan term and remaining maturity; existing floating rate loan indication, logarithmized collateral value, logarithmized loan amount, loan denominated in foreign exchange indication, loan denominated in HUF indication and subsidized loan indications (NHP and Szechenyi). Firm related controls are age (categories with 5-year buckets), size (micro, small, medium or not SME), legal entity type, county of firm's location and whether it is a foreign entity. Changes in the macroeconomic environment are controlled by the quarter fixed effects. For each variable (first column), the estimated coefficients and the standard error (in parentheses) are shown, as well as their p-values denoted by stars (*p<0.1; **p<0.05; ***p<0.01).*

Table A4: Survival analysis results using renewable energy firms outside the GPCR too

	(1)	(2)	(3)	(4)	(5)
All RE	-1.188***	-1.415***	-0.816**	-0.951***	-1.214***
	(0.289)	(0.303)	(0.346)	(0.347)	(0.412)
EM	-0.873***	-0.907***	-0.896***	-0.856***	-0.712***
	(0.214)	(0.214)	(0.214)	(0.215)	(0.226)

Leasing dummy				-0.187***	-0.117**
				(0.048)	(0.055)
Sales growth rate					0.040***
					(0.010)
Liquidity					-0.011
					(0.010)
Leverage					0.926***
					(0.101)
ROA (after tax)					-0.671***
					(0.129)
EBITDA to Equity ratio					-0.133***
					(0.050)
Sales to Assets					0.047***
					(0.014)
Credit related controls	No	No	No	Yes	Yes
Economic sector control	No	No	Yes	Yes	Yes
Firm related controls	No	Yes	Yes	Yes	Yes
Missing data control	No	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes
Observations	562,371	473,885	473,885	473,885	350,368
R2	0.0001	0.002	0.002	0.003	0.004
Max. Possible R2	0.130	0.139	0.139	0.139	0.136
Wald Test	33.470*** (df = 2)	909.240*** (df = 50)	1,040.200*** (df = 68)	1,435.780*** (df = 76)	1,292.170*** (df = 82)
LR Test	48.473*** (df = 2)	908.727*** (df = 50)	1,036.892*** (df = 68)	1,464.784*** (df = 76)	1,306.420*** (df = 82)
Score (Logrank) Test	36.628*** (df = 2)	953.980*** (df = 50)	1,093.578*** (df = 68)	1,501.141*** (df = 76)	1,343.004*** (df = 82)

*Note: Winners of renewable energy auctions are included too in the GPCR and other RE variable. Credit related controls include existing floating rate loan indication, logarithmized collateral value, logarithmized loan amount, loan denominated in foreign exchange indication, loan denominated in HUF indication and subsidized loan indications (NHP and Szechenyi). Firm related controls are age (categories with 5-year buckets), size (micro, small, medium or not SME), legal entity type, county of firm's location and whether it is a foreign entity. Changes in the macroeconomic environment are controlled by the quarter fixed effects. For each variable (first column), the estimated coefficients and the standard error (in parentheses) are shown, as well as their p-values denoted by stars (**p<0.1; **p<0.05; ***p<0.01*).*