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

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Green Firms Are Less Risky: Results from a Preferential Capital Requirement Programme in Emerging Europe

(A zöld cégek kevésbé kockázatosak: egy tőkekövetelmény-kedvezmény program eredményei)

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Contents

Abstract

This study evaluates the credit risk of sustainable loans in a preferential capital requirement programme. We utilise loan-level data from a uniquely implemented programme from Hungary, applying logistic regressions and survival analysis techniques. We observe a significantly reduced credit risk for firms with renewable energy and electromobility loans, even after accounting for all relevant covariates. Models incorporating green characteristics predict a substantially lower credit risk for firms with green loans compared to models excluding green characteristics. These results are economically significant and robust to model specifications, alternative definitions of green firms and varying default definitions. We show that green loans' lower probability of default can justify a reduction of several percentage points in capital requirements.

Journal of Economic Literature (JEL) codes: E58, G21, G33, O16
Keywords: sustainable finance, financial stability, capital requirement, green finance, default probability, green transition, central bank mandates

Kivonat

A tanulmány a fenntartható hitelek hitelkockázatát értékeli egy tőkekövetelmény- kedvezmény programban. Az elemzéshez egy egyedülállóan Magyarországon megvalósított program hitelszintű adatait használjuk, logisztikus regressziókat és túlélés elemzési technikákat alkalmazva. Jelentősen kisebb hitelkockázatot figyelünk meg a megújuló energia- és elektromobilitási hitelekkel rendelkező cégeknél, a releváns kontroll változók bevonása után is. A zöld jellemzőket tartalmazó modellek lényegesen alacsonyabb értéket becsülnek a zöld hitelekkel rendelkező cégek hitelkockázatára, mint a zöld jellemzőket nem tartalmazó modellek. Ezek az eredmények gazdaságilag is jelentősek, emellett robusztusak modellspecifikációra, zöld cégek alternatív definícióira és nemteljesítési definíciókra nézve is. Megmutatjuk, hogy a zöldhitelek alacsonyabb nemteljesítési valószínűsége a tőkekövetelményük több százalékpontos csökkentését indokolhatja.

Journal of Economic Literature (JEL) kódok: E58, G21, G33, O16
Kulcsszavak: fenntartható pénzügyek, pénzügyi stabilitás, tőkekövetelmények, zöld pénzügyek, csőd valószínűség, zöld átmenet, jegybanki mandátumok

1 Introduction

Climate change has emerged as a primary concern for both central banks and supervisory authorities. A variety of monetary policy instruments and prudential regulatory tools has been identified to support green finance initiatives. Several policy actions have been recommended, such as quantitative easing (QE) programmes aimed at limiting 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 the transition to a low-carbon economy is to adjust capital requirement regulations by incorporating green supporting factors (GSF) and dirty penalising factors (DPF). A GSF reduces the minimum amount of capital required to be held for exposures that qualify as green exposures. By contrast, a DPF prescribes higher capital buffers for loans to corporates with high GHG emissions. The simultaneous use of GSF and DPF may neutralise changes to the banking sector's overall capital requirements. The net effect of such changes may tilt funding (Fraisse et al., 2020; Gropp et al., 2019) towards sustainable activities and therefore support the transition to a climate-resilient economy.

Given that the primary objective of capital requirements is financial stability, these requirements are risk based. Consequently, the primary argument for implementing 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, either because of policy actions (such as subsidised feed-in tariffs for electricity generation or favourable taxes for electric vehicles), technological advancements in green areas (lower cost for PVs or batteries) or market changes due to customer demand. Secondly, firms with green loans signal an environmentally conscious management attitude and the capability to obtain complex products, which can improve credit performance as well. Additionally, some studies have found that sustainable firms have better financial performance than their peers and that ESG scores improve creditworthiness (Brogi & Lagasio, 2018; Carbone et al., 2021).

Although the debate about introducing such green tools to the microprudential framework started several years ago, few actual experiments have taken place. To the best of our knowledge, the green preferential capital requirement programme (GPCR) of the Magyar Nemzeti Bank (MNB, Central Bank of Hungary) has been the only implementation, at the time of writing.

In this paper, we assess the riskiness of firms with loans eligible for the GPCR (green firms) and compare them to similar, but non-green firms: corporates without any loans included in the programme. 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 2024. 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 based on estimated risk differentials between firms with green and non-green loans.

Our findings confirm that firms with renewable energy and electromobility loans under the MNB's green preferential capital requirement programme exhibit lower probability of default (PD) values compared to their peer groups or the overall sample. Even after controlling for relevant risk factors, the dummy of green loans significantly reduces default risk for firms across our model specifications. Using the estimates of our most saturated logistic model, information on renewable energy and electromobility loans imply a decrease of 1.5 and 1.7 percentage points in yearly PD, respectively. We also estimated the difference of green-informed and uninformed models' prediction for the two green portfolios, which confirmed that models with green information predict substantially smaller risk for such firms. At the same time, in itself the empirical PD difference explains several percentage points and around one half of the capital requirement discount, using a simplified fair capital requirement calculation, based on the formula recommended by Vasicek (2002).

This means that the GPCR in its actual form is an active central bank support to catalyse the transition process, and it should be constantly monitored in order to maintain prudential levels of banking capital.

Our paper is closely related to the literature examining the risk differential of green and brown activities. However, there are significant data gaps in sustainable finance, and 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, using sustainable indicators identified ex-post by the reporting financial institutions. Their results indicated that green loans generally carry lower credit risk, but they 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 the asset quality of banks due to the lower volatility of the borrowers' earnings (Umar et al., 2021). The importance of sustainability for operational risk is documented as well (Berlinger et al., 2021). On the retail side, the lower default risk of residential mortgages financing energy efficient housing has been demonstrated in many real estate markets (Guin & Korhonen, 2020; Billio et al., 2022). Higher energy use at loan-backed commercial properties also increases default rates (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. Empirical evidence on the effects of GSF or DPF implementation is limited. A paper by Miguel et al. (2024) 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 for loans with higher environmental risks. The authors found that the impacted large banks reallocated their lending away from exposed sectors, while also shortening the maturity of loans to these sectors. However, smaller banks, which are exempt from the regulation, expanded their credit supply and the maturity of loans to exposed sectors. The authors found only moderate impacts on the real economy and greenhouse gas emissions.

Others have focused mainly on the theoretical modelling 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, potentially posing risks to financial stability. The simultaneous implementation of GSF and DPF has the most significant impact on green and dirty investment differences by cancelling out real economy and financial stability issues. However, their effects alone are tiny. Optimal regulation may involve complementing GSF with further green finance policies such as 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 the empirical risk differential for sustainable firms for multiple reasons, in addition to 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 programme) and the reported data were supervised continuously by the central bank. Secondly, banks reported loans that are compliant with the GPCR programme. The programme's eligibility conditions closely follow the EU taxonomy, a well-known international standard for sustainability, which gives additional validity to our green variables. Thirdly, due to the GPCR's detailed obligatory reporting scheme, 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 participating in a preferential programme 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 similar calibration results on the impact of minimum capital requirements, particularly in the sustainability context.

Our findings are relevant for policymakers evaluating the risk basis 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 provided by this paper on the risk differential between green and non-green loans 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 firms may be impacted negatively. Empirical evidence has 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 funding for the green transition (Mueller & Sfrappini, 2022).

The remainder of the paper is structured as follows: Section 2 describes the institutional background of the programme, and Section 3 introduces the data sources we use and presents summary statistics. In Section 4, we detail the tools for empirical analysis and the formula to calibrate a fair level of capital discount. Our results and the limitations are discussed in Section 5, while Section 6 presents the conclusion.

2 Institutional background

In 2019, the MNB introduced a Green Programme to “mitigate the risks associated with climate change and other environmental problems, to expand green financial services in Hungary” (MNB, 2019). This programme encompassed a range of measures,[1] including educational initiatives and knowledge dissemination in green finance, as well as efforts to reduce the MNB’s ecological footprint. The MNB became the first European central bank with an explicit green mandate (Burger and Wójcik, 2024): pursuant to the Central Bank Act, the MNB is mandated to support environmental sustainability without compromising its primary objective, price stability.

In December 2020, the MNB launched the Green Preferential Capital Requirement Programme (GPCR) for sustainable corporate and municipal financing within the framework of the Basel Accords and EU banking regulations.[2] The programme 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 substantially expanded to include electromobility, sustainable agriculture and food industry, commercial real estate, energy efficiency projects and the acquisition or buyout of green business equity. Qualifying loans must meet one of these financing objectives and have an origination date after 1 January 2020. Eligibility criteria for each of these goals are aligned with the Hungarian adaptation of the EU Taxonomy, with adjustments for local data availability and contextual considerations. In November 2021, the GPCR was effectively expanded again, this time focusing on the green housing loans segment. Eligible loans can be used for the purchase or construction of a new, energy-efficient residential building and modernisation for the purpose of energy savings, in accordance with the EU Taxonomy.

This capital discount functions as a green supporting factor (GSF), allowing banks to deduct it from their Pillar II capital requirements. The discount ranges from 5 to 7 percent of each eligible gross exposure, dependent on the extent of their ‘greenness’. Loans and bonds which fulfil 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 programme is voluntary,[3] but participating banks must submit information on the loans and bonds included in the programme.

The GPCR has been very popular: in its first year, over 90 percent of all banks joined the programme. Exposures covered by the programme have been growing steadily, from 0.8 percent of NFC exposures (around EUR 225 million) in December 2020 to 4.6 percent (around EUR 1.54 billion) in June 2024. As a result of its success, the programme’s initial expiration year of 2025 was extended, and loans issued in 2025 may be eligible for capital discount for 5 consecutive years up until 2030.

One special aspect of this programme is the participation process. Borrowing firms applying for a loan are most often not even informed about the preferential capital treatment their creditor banks receive. Banks are incentivised to nudge clients towards fulfilling participation criteria, but otherwise there is no selection process in addition to a normal loan application. While one may argue that a prudent bank would select good debtors for the programme only, there are counter-arguments underscoring banks’ possible motivations not to use this pre-selection. Banks with a higher share of green loans, for instance, score better in a set of terms, including lower funding costs (Yameen et al., 2024). All in all,

[1] In addition, the Green Mortgage Bond Purchase Programme and the Green Home Programme were also introduced. These were launched in 2021, immediately following the publication of the Green Monetary Policy Toolkit Strategy (MNB, 2021).

[2] Hungary implements the bank regulations of the EU, which are 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, the MNB evaluates banks during the SREP process and oversees the setting and auditing of capital requirements.

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

we believe that using a green pledge given by the central bank to lower capital requirements is a low risk decision for participating banks with positive returns.

In other words, all loans financing such green goals are most likely included by incentivised banks, while other loans funding other goals are excluded (since they are not eligible). Thus, self-selection is primarily constrained to the financed activity and the timing of loan application. For this reason, we also show our results to firms with similar loans both in terms of loan amount and the timing of credit application.

The remainder of the paper details the GPCR data, compares default probabilities of firms with eligible and non-eligible loans, and calculates an equitable level of capital discount.

3 Data

The data used for the analysis are compiled from multiple sources. First, we use the MNB's Credit Register (HITREG). This database contains granular, loan-level information on all loans issued by Hungarian credit institutions. It also covers basic information on the collateral and the debtor, which we merged with the loan-level data. The data span from Q1 2020 to Q2 2024, reported quarterly. Second, we incorporate auxiliary reports from the green preferential capital requirement programme, linked via the same identifier used in the Credit Register. Third, we combine the credit data with the corresponding firms' financial statements. Firm-level financial variables were available for 71 percent of the loans.[4] Each year, we derive financial variables from the previous year's balance sheet data. Finally, we use data on auction winners from Hungary's renewable feed-in tariff auctions (2012–2022) to proxy other renewable energy firms.

Due to the COVID-19 pandemic, retail and business loans issued before 18 March 2020 qualified for a repayment moratorium.[5] Since defaults were precluded for loans in moratorium, we focus on loans issued after this date and exclude pre-COVID loans. Excluding loans issued before the study period, the dataset comprises 3.2 million unique loan IDs.[6] Given the short average maturity of the loan portfolio, the number of loan IDs increased from approximately 10,000 at the first reporting date to 230,000 by early 2022, when their numbers stabilised. After aggregating loan IDs at the firm level, we observe 891,000 credit performance data points, of which 619,000 include financial statement data.

A loan was classified as in default on a given date if it met the Capital Requirements Regulation (CRR) Article[7] 178 criteria within the subsequent three months. These criteria include situations where the credit institution deems the obligor unlikely to fulfil credit obligations or when the obligor is over 90 days past due on any substantial credit obligation. To minimise technical defaults, a minimum of 10 percent of a firm's outstanding principle had to be in default, as per 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 1.1 percent to 0.8 percent.

[4] We did not use financial information on sole entrepreneurs and firms not subject to corporate tax.

[5] The scheme was automatically applicable to all debtors subject to the legislation, and debtors preferring not to remain in the scheme had the option to opt out. One year later, many corporates (39 percent of the portfolio) were still participating in the moratorium (Dancsik and Fellner, 2021), but at the beginning of 2023 the scheme ended.

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

[7] 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.

Table 1
Summary statistics

Variable	No. obs	Mean	Std Dev	Min	25th per.	Median	75th per.	Max
Default event (unfiltered)	890 872	0.011	0.103	0	0	0	0	1
Default event (filtered)	890 872	0.008	0.086	0	0	0	0	1
Firm age	890 872	15.865	7.279	0.42	10.77	15.98	19.68	82.26
Foreign firm (dummy)	890 872	0.020	0.138	0	0	0	0	1
Micro firm (dummy)	890 872	0.631	0.482	0	0	1	1	1
Small firm (dummy)	890 872	0.216	0.411	0	0	0	0	1
Medium firm (dummy)	890 872	0.056	0.230	0	0	0	0	1
Large firm (dummy)	890 872	0.089	0.285	0	0	0	0	1
Energy sector (dummy)	890 872	0.006	0.077	0	0	0	0	1
Sales growth rate	618 916	0.451	1.747	-1.00	-0.05	0.13	0.41	16.74
Leverage	636 563	0.475	0.249	0.00	0.28	0.47	0.67	0.98
Liquidity	636 563	2.884	2.683	0.00	1.13	1.85	3.53	10.00
EBITDA-to-equity ratio	636 563	0.383	0.457	-2.25	0.16	0.32	0.56	2.48
ROA (after tax)	636 563	0.103	0.209	-3.00	0.02	0.07	0.18	0.80
Sales-to-assets	636 563	1.717	1.521	0.00	0.75	1.35	2.20	11.56
Elapsed loan term	890 872	1.243	0.895	0.00	0.50	1.06	1.85	4.040
Remaining maturity	890 872	3.404	2.940	-2.57	1.82	3.01	3.84	30.00
Log of credit size	890 872	2.877	2.014	-4.61	1.79	2.77	3.97	17.44
Log of collateral value	890 872	-0.249	3.670	-4.61	-4.61	0.96	2.52	12.08
Collateral (dummy)	890 872	0.301	0.459	0	0	0	1	1
HUF loan (dummy)	890 872	0.978	0.147	0	1	1	1	1
FX loan (dummy)	890 872	0.046	0.209	0	0	0	0	1
Floating rate (dummy)	890 872	0.405	0.491	0	0	0	1	1
NHP loan (dummy)	890 872	0,131	0.338	0	0	0	0	1
Szechenyi loan (dummy)	890 872	0.453	0.498	0	0	0	0	1
Leasing loan (dummy)	890 872	0.326	0.469	0	0	0	1	1
GPCR (dummy)	890 872	0.035	0.184	0	0	0	1	1
GPCR: Renewable Energy	890 872	0.007	0.084	0	0	0	0	1
GPCR: Electromobility	890 872	0.028	0.164	0	0	0	0	1
All renewable energy	890 872	0.012	0.108	0	0	0	0	1

Note: Observations are at the quarter – firm level, from the period 2020–2024. The first column contains the variable names, while the following columns show 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.

Explanatory variables include macroeconomic, credit-related, and firm-level financial data. Credit-related variables include loan amount, collateral value, time to maturity, contractual interest rate, foreign currency denomination (as a dummy variable) and loan purpose. Firm-level information are age, size, economic sector (NACE 3 digits) and legal entity type. Additionally, we consider the county (NUTS-3 region[8]) of firm location and whether over 50 percent of firm equity is foreign-owned. We create leverage, liquidity, ROA, EBITDA-to-equity and sales-to-assets indicators based on the firms' financial statements (see Appendix Table A1). We choose these variables based on the relevant international (Altman, 1968; Neagu et al., 2023) and Hungarian credit risk literature (Banai at al., 2016; Burger, 2022). The primary variables

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

of interest are two dummy variables: whether a firm holds any loans in the preferential requirement programme as Renewable Energy (RE) or Electromobility (EM) loans during the observation period.

Table 1 reveals that 0.7 percent of the observations (6,720 instances) involve firms with RE loans, closely matching the Energy sector's 0.6-percent share in the sample. Notably, there is some overlap: 67 percent of Energy sector firms have RE loans, although several firms outside this sector also hold such loans. Firms with electromobility-related loans account for 2.8 percent of observations (24,713 instances), substantially lower than the 32.6-percent share held by firms with leasing loans.

4 Methodology

We apply two econometric techniques to evaluate the impact of green loans on default probability. First, we use traditional logistic regression. Next, we apply survival analysis, estimating extended Cox proportional hazard models. Logistic regression has the advantage of being widely used and easily interpretable, estimating covariate effects and fitted default probabilities. By contrast, survival analysis excels at handling censored data (Stepanova & Thomas, 2000) and capturing risk term structures. Survival analysis is common in medical research due to its higher statistical power compared to logistic regression (van der Net, 2008) and is gaining popularity in financial modelling 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:

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

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

SURVIVAL ANALYSIS

Survival analysis focuses on the time until a performing loan defaults post-origination, 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 the calendar year. A possible way to model the distribution of *T* is introduce the hazard function of default risk, *h*(*t*).

$$h(t) = \lim_{\Delta t \to 0} \frac{Prob(t \leq T < t + \Delta t \ \ |t \leq T)}{\Delta t} \tag{2}$$

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: .

The Cox proportional hazard model (Cox, 1972) evaluates covariate relationships with the survival distribution via the hazard function. The model assumes that the hazard of firm *i* with the attributes 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.

$$h(t, \boldsymbol{x_i}(t)) = \exp\left(\beta' \boldsymbol{x_i}(t)\right) \cdot h_0(t) \tag{2}$$

Each characteristic's coefficient determines the hazard ratio ($exp(\beta' x_i(t))$). A ratio above (below) 1 indicates a higher (lower) probability of default relative to the baseline hazard ($h_0(t)$).

One key strength of survival analysis is its capacity to handle time-varying risk, which is crucial in credit risk analysis where default risk in the first few years of the loan is substantially higher than later. Another advantage of this framework is that loans originating before or extending beyond the observation period can still be included in the analysis. In the case of early origination, the data is called left-censored (or truncated), and in the case of late maturity the data is called right-censored. Since we almost exclusively include loans originated in the observation period, right-censored data are a more relevant issue in our case.

FAIR CAPITAL REQUIREMENTS

Capital requirements are risk based; specifically, the Basel framework's Pillar I regulatory capital is grounded in the Asymptotic Single Risk Factor (ASRF) model by Vasicek (2002). While the implementation of final capital requirements is more complex than the ASRF model, this model does provide a useful foundation for calculating PD's impact.[9] The assessment can provide the theoretical threshold for the minimal capital a bank needs to keep in order to limit their default probability to 0.1 percent or less in a year. This translates into sufficient capital to cover unexpected losses in 999 years out of 1000. This is referred to as the 'fair' capital requirement. The ASRF formula is the following:

$$Fair\ Cap\ Req = LGD \cdot \left(\Phi\left(\sqrt{\frac{1}{1-R}} \cdot \Phi^{-1}(PD) + \sqrt{\frac{R}{1-R}} \cdot \Phi^{-1}(0.999) \right) - PD \right) \cdot M\_adj \tag{4}$$

whereby

- (Φ) 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 apply the ASRF formula, as a function of PD, to measure 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).

[9] There are several 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 standardised approach calculate capital based on predefined values.

5 Results

5.1 FIRMS WITH GREEN LOANS

We analyse the characteristics of firms that receive green loans in greater detail. We employ logit models with a binary dependent variable indicating whether the firm received an RE or EM loan within the observation period. The results show (Table 3, left side) that RE firms tend to be significantly younger, larger and more frequently foreign-owned. They tend to borrow more and have higher leverage, but their loans have higher collateralisation. RE firms are associated with higher sales growth and EBITDA-to-equity ratios, although asset-based profitability measures are lower relative to other firms. RE firms in the GPCR are overall are really similar to other renewable energy firms based on our results (see Table A7 in Appendix), which shows that self-selection for participation in the programme is unlikely among sustainable firms. Firms with EM loans (Table 3, right side), by contrast, have lower leverage, their profitability measures are significantly higher (both asset and equity-based) and they tend to be smaller firms. They seem to be less liquid but have more collateral as well.

Table2
Logit regressions on Renewable Energy generation and Electromobility firms

	Dependent variable:					
	GPCR RE			GPCR EM		
	(1)	(2)	(3)	(4)	(5)	(6)
Firm age	-0.023***	-0.014***	-0.007***	0.001	0.003**	0.003***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Micro firm	-0.342***	-0.937***	-0.065	1.611***	0.687***	0.518***
	(0.053)	(0.068)	(0.074)	(0.05)	(0.061)	(0.065)
Small firm	-0.24***	-0.774***	-0.428***	2.011***	1.079***	0.602***
	(0.066)	(0.077)	(0.081)	(0.051)	(0.061)	(0.064)
Medium firm	1.17***	0.43***	0.101	1.941***	1.06***	0.454***
	(0.066)	(0.076)	(0.077)	(0.056)	(0.065)	(0.066)
Foreign firm	0.856***	0.661***	0.616***	-0.763***	-0.793***	-0.864***
	(0.07)	(0.075)	(0.078)	(0.074)	(0.075)	(0.076)
Sales growth rate		0.032***	0.015**		0.002	-0.009**
		(0.007)	(0.007)		(0.004)	(0.004)
Liquidity		-0.033***	-0.012		-0.025***	-0.027***
		(0.008)	(0.008)		(0.004)	(0.004)
Leverage		0.732***	0.142*		-0.352***	-0.433***
		(0.079)	(0.082)		(0.045)	(0.047)
ROA (after tax)		-0.495***	-0.683***		0.526***	0.229***
		(0.096)	(0.12)		(0.055)	(0.055)
EBITDA-to-equity ratio		0.356***	0.394***		0.516***	0.357***
		(0.033)	(0.035)		(0.022)	(0.023)
Sales-to-assets		-1.369***	-0.953***		-0.123***	-0.071***
		(0.038)	(0.036)		(0.006)	(0.006)
Log of instrumentum size			0.373***			0.185***
			(0.013)			(0.007)
Log of collateral value			0.041***			0.042***
			(0.005)			(0.004)
Observations	890,872	618,916	618,916	890,872	618,916	618,916

*Note: The table presents model results explaining if firms are in the GPCR programme. 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, and 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).*

5.2 DEFAULT PROBABILITIES

The observed quarterly default rates for the whole sample are 75 bps, while they are only 24 bps for RE and 27 bps for EM. In other words, when not controlling for other factors, green firms are less risky. However, several covariates have an impact on risk, and our goal is to isolate the impact of established risk factors from that of RE and EM information. By incorporating these covariates, we estimate the incremental information value of green loans on corporate PD.

The results of the estimated logistic regressions are presented by Table 4. We estimated several models to obtain more robust results and to isolate the effect of RE and EM on corporate default risk. Control covariates are organised into the following broad categories: macro environment, basic firm data, sector and credit-related and financial statement-based information; the covariate groups are introduced stepwise. Model (1) estimates the effect of RE and EM on PD without additional covariates. 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 the first three digits of the NACE sectoral classification. 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). With this step-by-step approach we can detect if the lower risk of RE firms disappears.

Table 3
Logistic regression estimates on the impact of green information on corporates' probability of default

	(1)	(2)	(3)	(4)	(5)
GPCR RE	-1.174***	-1.437***	-0.670**	-0.800***	-0.694**
	(0.259)	(0.260)	(0.281)	(0.283)	(0.291)
GPCR EM	-1.062***	-1.132***	-1.126***	-0.931***	-0.829***
	(0.124)	(0.124)	(0.124)	(0.125)	(0.149)
Leasing dummy				-0.326***	-0.191***
				(0.034)	(0.043)
Sales growth rate					0.011
					(0.009)
Liquidity					-0.035***
					(0.008)
Leverage					0.874***
					(0.074)
ROA (after tax)					-1.122***
					(0.051)
EBITDA-to-equity ratio					-0.191***
					(0.030)
Sales-to-assets					-0.085***
					(0.013)
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	890,872	890,872	890,872	890,872	618,916
Akaike Inf. Crit.	78,813.480	77,449.200	77,042.500	75,788.880	46,035.590
AUROC	0.5114	0.6370	0.6643	0.7030	0.7254

*Note: Credit-related controls include longest elapsed loan term and remaining maturity, existing floating rate loan indication, logarithmised collateral value, logarithmised loan amount, loan denominated in foreign exchange indication, loan denominated in HUF indication and subsidised 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 RE coefficients indicate that firms in the RE programme exhibit a lower probability of default values. Coefficient estimates are in the range of -1.44 to -0.7, which corresponds to odds ratios between 24 and 50 percent. This range implies a risk reduction for an average firm of somewhere between 37 and 58 bps (1.49 and 2.27 pps) in quarterly (yearly) PD. The coefficient remains statistically significant across all models. Even in Model (5), where all variables describing the financial situation of the firm are controlled for, the RE dummy's coefficient is highly significant. It is important to emphasise that the RE dummy remains significant even after controlling for the economic activity of firms. The discriminant power of Model (5) is sufficient based on the 72.54-percent value for the area under the ROC curve (AUROC) measure.

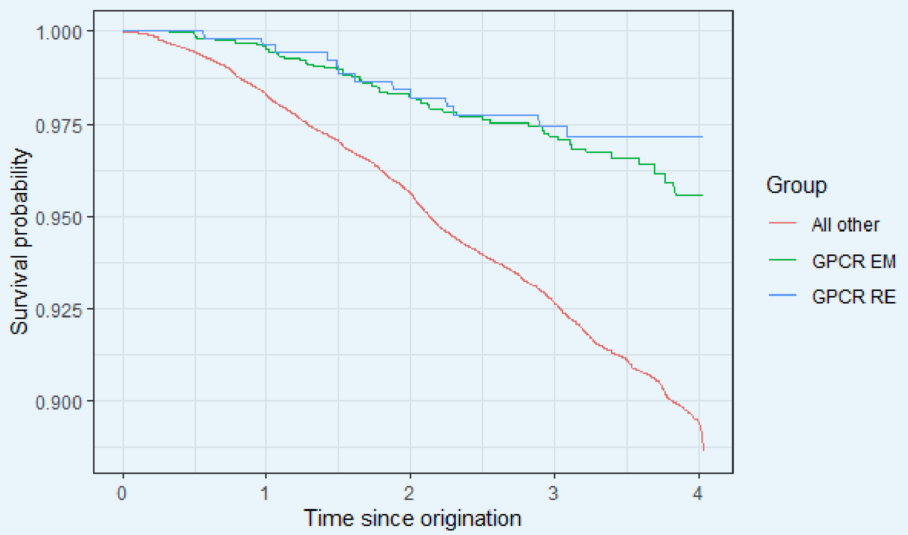
Average marginal effects (AME) are substantial in most models, as RE firms are younger and relatively smaller, but empirically less risky than other firms. Young firms exhibit substantially higher risk, with mature firms (15–35 years old) approximately 45 bps less risky than young firms (<5 years old), according to the AME metric. Micro and small enterprises are around 20 basis points riskier compared to large corporates. However, greenness seems to compensate for these other credit risk factors, as AME for RE and EM decreases PD by 32 and 37 bps, respectively.

Our results also show that the EM dummy has a negative coefficient, meaning that EM firms exhibit lower probability of default, holding all else equal. All of our estimated models suggest that this effect is statistically significant (even at a 1-percent level). The coefficient estimates range from -0.83 to -1.13, which imply that it is a stable effect. The impact of EM dummy odds ratios (32–43 percent) on an average firm's quarterly PD ranges from 43 to 51 bps (1.68 to 2.02 pps yearly). If we control for firms which are expected to be similar via the leasing loan indicator, the results do not change, and EM remains significant (Model (4)-(5)). Whether the credit information or financial state of firms is included also does not affect the estimates. Similarly to RE, if only RE and EM information is part of the model, the coefficients are significantly negative.

To robustly assess the information value of greenness, we estimate the difference between two model predictions with and without the green indicator for both green portfolios. First, all explanatory variables apart from the green indicators were included (similarly to Model (5)) and compared the predictions' differences with Model (5). For RE and EM portfolios, we see a 55-bp and 79-bp difference, respectively, between the two predicted median PDs, suggesting that the predictions of the model without the green indicator are upward biased for green firms.

Before analysing the results of the Cox model, the validity of the proportional hazard assumption is addressed. Figure 1 shows that the probability of survival for both RE and EM is consistently higher than for other firms. This aligns with the logistic regression results, particularly those in Model (1). Additionally, it implies that the proportional hazard assumption is not falsified, as the groups' survival functions do not cross.

Figure 1
Kaplan-Meier survival probabilities for RE, EM and other firms



Note: RE firms' survival probabilities are denoted by blue, EM firms' survival probabilities are denoted by green, all other firms by red. 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 assumes no firm 'recovery' events. Moreover, only hazard *ratios* are estimated; hence, the direct effect of explanatory variables on the absolute hazard is not captured.

Table 5
Survival analysis estimates on the impact of green information on corporates' time to default

	(1)	(2)	(3)	(4)	(5)
GPCR RE	-1.158***	-1.360***	-0.575*	-0.733**	-0.755**
	(0.278)	(0.278)	(0.303)	(0.303)	(0.316)
GPCR EM	-0.973***	-1.012***	-1.010***	-0.906***	-0.879***
	(0.131)	(0.132)	(0.133)	(0.133)	(0.150)
Leasing dummy				-0.249***	-0.181***
				(0.038)	(0.043)
Sales growth rate					0.033***
					(0.007)
Liquidity					-0.014*
					(0.008)
Leverage					0.924***
					(0.076)
ROA (after tax)					-0.708***
					(0.066)
EBITDA-to-equity ratio					-0.167***
					(0.033)
Sales-to-assets					0.021*
					(0.011)
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	877,178	776,207	776,207	776,207	575,025

*Note: Credit-related controls include existing floating rate loan flag, logarithmised collateral value, logarithmised loan amount, flag for loan denominated in foreign exchange, flags for the loan denominated in HUF and for subsidised 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 RE coefficient estimates corresponds to relative hazard ratios of 56 and 26 percent, respectively, while our most detailed Model (5) implies a hazard ratio of 47 percent for RE. This means that the hazard of RE firms is lower compared to similar firms by a value between 44 and 74 percent – as described by the different models. The coefficients of EM are significant and more robust than those of the logistic regression results. The estimates are between -0.88 and -1.01, implying hazard ratios within the range of 41.5 and 36 percent, which corresponds to a decline of hazard in the range of 58.5 to 64 percent.

5.3 ROBUSTNESS ASSESSMENT OF RISK DIFFERENTIALS

One main limitation of the analysis is the low number of green energy firm defaults. To offset this limitation, we evaluate the robustness of our results by increasing the sample of green-default firms via two approaches. Firstly, we estimate the same logistic regression models using an 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 must 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 in the analysis on the winners of renewable energy auctions supported by the government from 2012 to 2022. As a result, the number of green renewable energy observations in the sample almost doubles (rising to 10,504). This part of the analysis confirms that renewable energy firms are less risky overall, not only those that are included in the capital requirement programme.

Table A3 and A4 illustrate the results of the new two sets of logistic regressions, while Table A5 presents the estimates of the extended Cox model with more green energy firms outside of 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 summarised 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 indicates that RE loans in the programme are not unique, as other RE firms in the sample also exhibit lower default risk. Overall, our results are robust and do not depend on the specific definitions of default or the RE identification criteria. The results of the survival analysis support these findings as well; see Appendix Table A5.

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			-0.550***
			(0.202)
GPCR RE	-0.694**	-0.606**	
	(0.291)	(0.280)	
GPCR EM	-0.829***	-0.615***	-0.828***
	(0.149)	(0.132)	(0.149)
Leasing dummy	-0.191***	-0.306***	-0.191***
	(0.043)	(0.041)	(0.043)
Sales growth rate	0.011	0.022***	0.011
	(0.009)	(0.007)	(0.009)
Liquidity	-0.035***	-0.035***	-0.035***
	(0.008)	(0.007)	(0.008)
Leverage	0.874***	0.741***	0.875***
	(0.074)	(0.065)	(0.074)
ROA (after tax)	-1.122***	-0.881***	-1.123***
	(0.051)	(0.046)	(0.051)
EBITDA-to-equity ratio	-0.191***	-0.190***	-0.191***
	(0.030)	(0.028)	(0.030)
Sales-to-assets	-0.085***	-0.108***	-0.085***
	(0.013)	(0.011)	(0.013)
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	618,916	618,916	618,916
Akaike Inf. Crit.	46,035.6	53,564.5	46,033.8

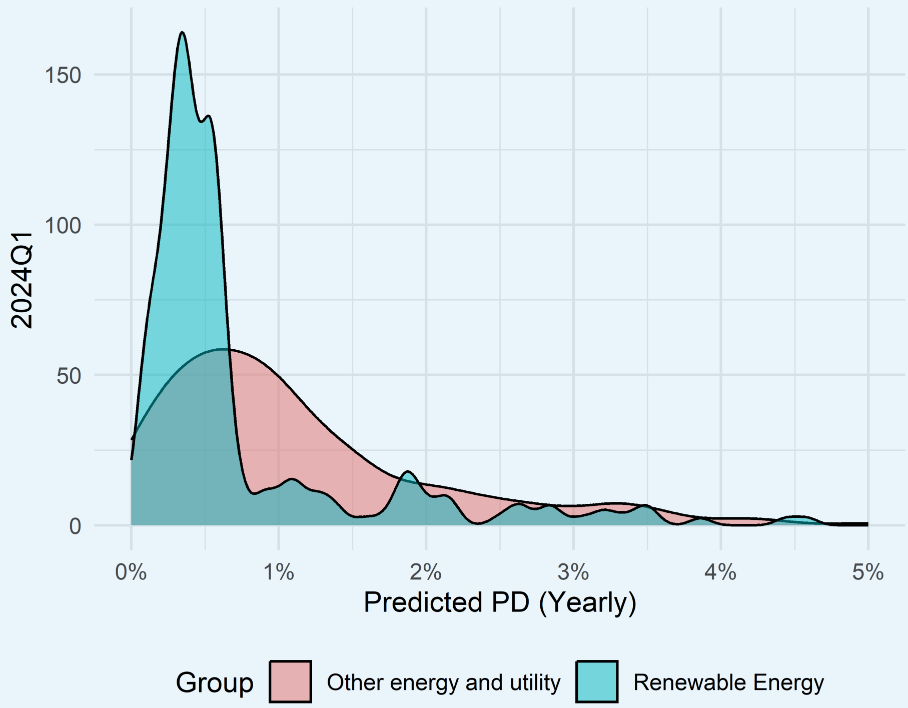
*Notes: The variable 'GPCR and other RE' includes the winners of renewable energy auctions, in addition to the firms in the RE:GPCR programme. Unfiltered default: any loan default implies firm default.[10] Credit-related controls include longest elapsed loan term and remaining maturity, a flag if any of the existing loans was a floating rate loan, the logarithm of the collateral value, the logarithm of the (authorised) loan amount, a flag if the loan is denominated in foreign currency, a flag if the loan denominated in HUF[11] and flags if the loan was subsidised (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-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).*

[10] The filtered default definition requires that at least 10 percent of a firm's loan exposure be in default.
[11] While most firms have HUF-denominated loans only (96 per cent), around 2 per cent of them have FX-denominated loans only or have both.

The results hold if we estimate separate logit models for micro and non-micro sized firms. We estimated the usual specification of our models and obtained the result that both green information dummies have a consistently negative effect on default probabilities in all of the models (Table A6 in the Appendix). It seems that the information value of greenness, especially for RE is more pronounced for smaller firms. The magnitudes of the size-specific estimates are similar to previous ones, but RE estimates in the case of non-micro firms are not significant in some models. Note, however, that in the case of non-micro firms we have even fewer observations for RE.

To evaluate whether sustainable loans carry lower overall risk, we compare their estimated PD distributions to those of 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 in Figure 2 for energy and utility firms and in Figure 3 for firms with leasing contracts. The distributions of estimated PDs show that RE and EM firms are less risky in general compared to their peers.[12]

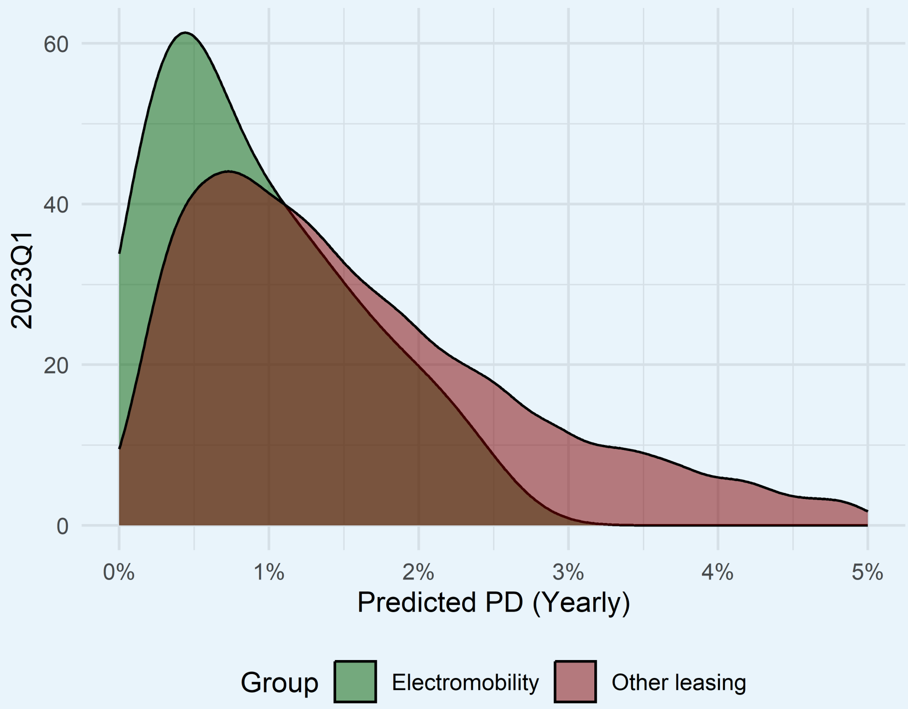
Figure 2
Predicted PD for energy and utility firms in Q1 2024



Note: Estimations are based on Model (5) for RE firms and other energy firms in the last quarter of the sample (Q1 2024). Default probabilities were converted to yearly values.

[12] 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.

Figure 3
Predicted PD for electromobility and other firms with leasing loans in Q1 2024



Note: Estimations are based on Model (5) for EM firms and firms with other leasing loans in the last quarter of the sample (Q1 2024). Default probabilities were converted to yearly values.

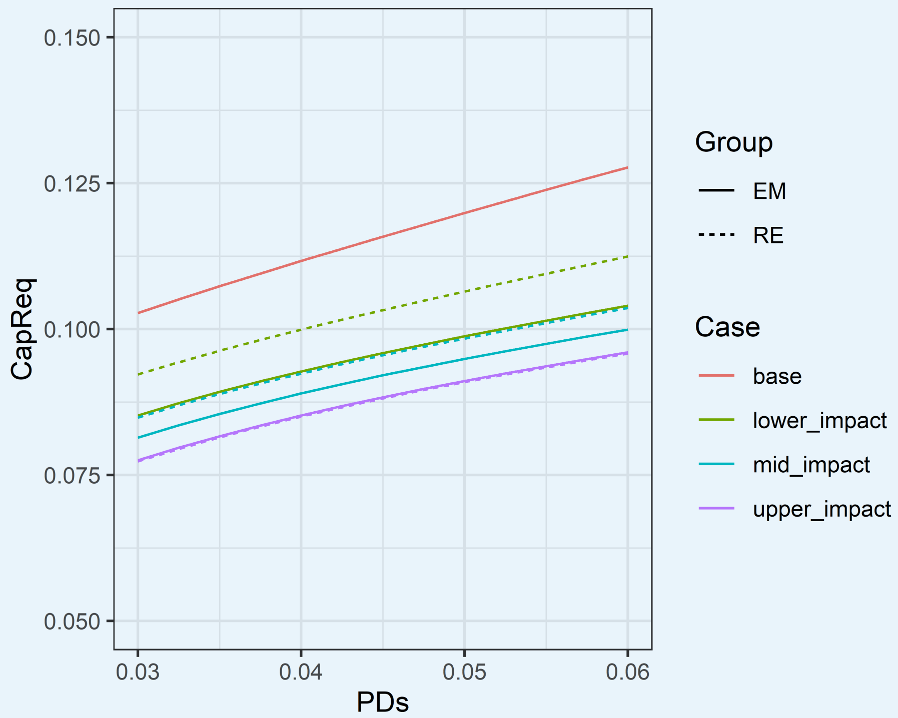
While the risk differential for RE firms and corporates with electromobility loans seems to be stable, the reason for this is not trivial. We argue that there are different reasons for the two groups of green loans. In the case of RE firms, substantial favourable policy measures have been implemented in Hungary, such as subsidised feed-in tariffs. Winners of feed-in tariff auctions can obtain steady revenue with little variation in cash flows, which could build a theoretical foundation for our result of lower default risk. This theory is in line with our robustness check where we included more feed-in tariff auction winner firms. For firms with EM loans, there are also some favourable policy measures in place (exemptions from vehicle and company car tax, parking fee discounts), but they seem to be less sizeable. In their case, we suppose that other factors, such as the firms' ESG attitude might be more important, as Brogi & Lagasio (2018) showed that better ESG performance is associated with higher profitability.

5.4 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 a range of likely values using their 1 standard deviation intervals. We calibrate the capital impact for both RE and EM. Results of the capital calibrations are shown in Figure 4.

The broad range of possible impacts on fair capital requirement is between 1.8 and 3.2 percentage points for EM and between 1.1 and 3.2 percentage points for RE. With a plausible, but conservative value of 5 percent as a through-the-cycle PD for corporates, the estimated odds ratios would imply a fair capital impact between 2.1 and 2.9 percentage points for EM (2.5 for the point estimate), and between 1.4 and 2.9 percentage points for RE (2.2 for the point estimate).

Figure 4
Fair capital requirements for the corporate segment as a function of PD



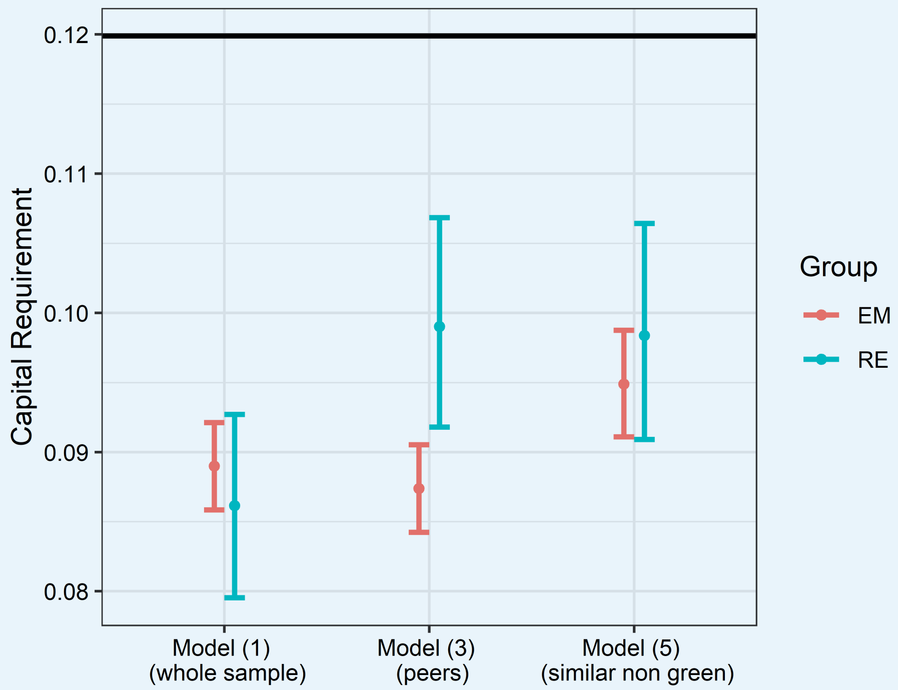
Note: Results based on the range of logit Model (5)'s odds ratios, a lower bound of 66.8 and an upper bound of 37.3 percent for RE firms and a lower bound of 50.7 and an upper bound of 37.5 percent for EM firms. Dotted line represents fair capital requirements for RE, solid lines for EM.

It is not self-evident that capital impact calculations should rely on the differential between green and comparable non-green firms, as in Model (5). The majority of the banks use the standardised approach (SA) to calculate capital in Hungary and in most emerging economies. These approaches also aim to be risk sensitive, but lack the accuracy of the 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 are shown in Figure 5, using a PD of 5 percent.[13] These findings indicate minimal differences among the cases. Capital impacts based on risk difference to the whole sample are larger for both RE and EM (3.4 and 3.1 percentage points, respectively), while the effects based on their peers are smaller for RE (2.1 percentage points), but very similar for EM (3.3 percentage points). Uncertainties around our calibrations are similar to those presented before, and they are overall somewhat larger for RE.

[13] The level of TTC PD has a little impact on our results, and the fair capital requirement differences are stable across different PDs as can be seen in Figure 4.

Figure 5
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.

Overall, substantial uncertainties remain regarding a fair capital deduction or supporting factor based on the estimated risk differential between green and non-green assets. However, it seems that around half of the 5-percent discount might be justifiable on these estimated risk differentials, or slightly less if one takes a more conservative approach and uses our lower bound estimates. At the same time, a 7-percent discount only seems to be justifiable based on our upper bound estimates. Note that these estimates are based entirely on historical data. Transition risks are expected to rise in 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 may decrease for other reasons. Additionally, since exposures are eligible to discount only for 5 consecutive years in this programme, portfolios with longer maturities have effectively lower discounts on average during their term.

5.5 LIMITATIONS

One primary limitation of our analysis is the relatively short sample period, restricted by the programme's duration. However, even this shorter period includes two recessions, and transition shocks, such as a large energy price shock in 2022 and a substantial carbon price increase in the EU ETS between 2020 and 2022. The frequency and intensity of such transition risks may increase along a net-zero pathway, likely widening the risk differential.

Another concern refers to two types of selection biases. The first is the potential self-selection bias, as green firms in our sample chose to adopt green technologies. While this bias is possible, our primary focus is to estimate the information value of firms having green loans (and participating in a capital deduction programme) on default risk, specifically the risk differential compared to peers. This is sufficient to decide on the risk-based nature of a preferential capital treatment. At the same time, our results should not be interpreted as estimates of the treatment effects of firms transitioning to sustainable technologies on default risk. While that is also an interesting research question, it is not essential or directly relevant for assessing capital deduction decisions. Another possible area for self-selection is that strong firms were more likely to invest and hence apply for investment loans during and shortly after the COVID-19 crisis, and loans in the programme were usually investment loans. We argue this selection does not bias our estimates for multiple reasons. All of our observations are for firms with newly originated loans. We directly control for firms with leasing loans, which are similarly confident to those in the EM group. For RE firms, we control for credit size, leverage and collateral, all of which are closely related to investment decisions and confidence, and hence bias through this channel is also unlikely.

The second potential selection bias refers to prudent banks singling out good firms only for the programme. Firstly, our results showed that other RE firms not included in the programme had also lower default risk, which implies no selection from the banks' side. Secondly, the opposite may also be true: banks may be keen to report as many firms green as possible in order to reduce overall funding costs (not just capital requirements). Overall, we argue that they simply classify eligible companies into the programme, when they qualify, and exclude them if they do not.

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 of the 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 the 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.

6 Conclusion

Capital requirements are risk-based, and thus understanding the risk profile of green loans is essential to evaluate the adequacy of their preferential treatment in the microprudential framework. This study examines the credit risk performance of firms with renewable energy and electromobility loans within Hungary's unique green preferential capital requirement programme. Participating banks receive preferential capital rates for eligible green loans. We use logistic regression and extended Cox proportional hazard models to assess default probability for green firms.

We find that renewable energy firms participating in the programme tend to be younger and more indebted. These firms show higher equity and sales-based profitability compared to peers. We find that firms with electromobility loans have lower leverage, with significantly higher asset and equity-based profitability than comparable firms.

We provide first evidence that loans in a green capital programme 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, after controlling for relevant risk factors and firm characteristics, firms with renewable energy and electromobility loans still show lower default probabilities. The estimated risk differential is both statistically and economically significant. We find that models lacking green information predict significantly higher default probabilities for renewable energy or electromobility firms compared to 'green-informed' models. Our results are robust across estimation methodologies, sustainability identification and default definitions.

Using a simplified capital requirement formula (based on an asymptotic single risk factor model), we show that while uncertainties are substantial in relation to a risk-based capital deduction for green loans, around one half of this discount is justifiable based on our results. Although the capital discount in this framework is generous, a reduction of several percentage points is justified solely by empirical risk differences, even without forward-looking risk considerations.

Our results are relevant for supervisors exploring appropriate green tools to introduce in capital requirements. These findings may also guide policymakers on the expected risk costs of green credit guarantee schemes. While we believe these findings offer valuable insights for international discussion on sustainable finance policy tools, we also acknowledge the limitations of our analysis.

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8 Appendix

Table A1
Definition of variables

Variable	Definition
Default event (unfiltered)	Obligor is considered unlikely to fulfill credit obligations or is over 90 days past due
Default event (filtered)	Firm is considered unlikely to fulfill credit obligations or is over 90 days past due, on more than 10 percent of the firm's outstanding principal
Firm age (years)	Age of firm in years
Foreign firm (dummy)	Binary indicator whether the firm is foreign
Micro firm (dummy)	Binary indicator whether the firm is micro
Small firm (dummy)	Binary indicator whether the firm is small
Medium firm (dummy)	Binary indicator whether the firm is medium
Large firm (dummy)	Binary indicator whether the firm is large
Energy sector (dummy)	Firm operates in NACE Code 35 (Electricity, gas, steam and air conditioning supply)
Sales growth rate	Revenue growth rate, winsorised at 1th and 99th percentile
Leverage	1 – equity / total assets, capped at 1 and floored at zero, winsorised at 1th and 99th percentile
Liquidity	Current assets divided by short-term debt, winsorised below -10 and above 10
EBITDA-to-equity ratio	Operating profit plus depreciation, divided by total equity, winsorised at 1th and 99th percentile
ROA (after tax)	After tax income as a percentage of total assets, winsorised at 1th and 99th percentile
Sales-to-assets	Revenues / total assets, winsorised at 1th and 99th percentile
Elapsed loan term	Longest elapsed loan term of the company
Remaining maturity	Longest remaining maturity of the company
Log of credit size (HUF)	Logarithm of instrumentum size in million Hungarian forint
Log of collateral value (HUF)	Logarithm of all collateral value in million Hungarian forint
Collateral (dummy)	Binary indicator whether the firm has any collateralised loans
HUF loan (dummy)	Binary indicator whether the firm has any loans denominated in Hungarian forint
FX loan (dummy)	Binary indicator whether the firm has any loans denominated in foreign currency
Floating rate (dummy)	Binary indicator whether the firm has any floating rate loans
NHP loan (dummy)	Binary indicator whether the firm has any supported loans in the NHP scheme
Szechenyi loan (dummy)	Binary indicator whether the firm has any supported loans in the Szechenyi scheme
Leasing loan (dummy)	Binary indicator whether the firm has any leasing loans
GPCR (dummy)	Binary indicator whether the firm has any loans in the GPCR
GPCR: Renewable energy	Binary indicator whether the firm has any RE loans in the GPCR
GPCR: Electromobility	Binary indicator whether the firm has any EM loans in the GPCR
All Renewable energy	Binary indicator whether the firm has any RE loans in the GPCR or has won renewable energy auction

Table A2
Descriptive statistics across NACE sectors

Sector	No. obs	Sector ratio	RE ratio (%)	EM ratio (%)	Green ratio (%)	Default rate (filt., %)
Agriculture, forestry, fishing	38,812	4.36	0.64	0.19	1.41	0.87
Mining and quarrying	813	0.09	1.85	0.00	1.85	0.86
Manufacturing	96,453	10.83	0.46	0.80	2.96	0.76
Electricity, gas, steam	5,299	0.60	67.47	0.25	67.96	0.21
Utility	3,256	0.37	0.00	0.71	2.83	0.55
Construction industry	105,261	11.82	0.22	1.02	2.92	1.20
Trade and repair of vehicles	200,554	22.51	0.13	1.12	3.12	0.69
Transportation and storage	39,439	4.43	0.15	0.89	2.53	0.82
Accommodation and food	29,488	3.31	0.26	0.97	3.09	0.77
Information and com.	24,640	2.77	0.00	2.52	5.43	0.76
Fin. and insurance activities	4,453	0.50	0.63	1.77	3.93	0.40
Real estate activities	32,728	3.67	0.71	1.34	3.54	0.65
Prof., scientific activities	63,327	7.11	0.24	1.76	4.18	0.69
Admin. and support services	30,243	3.40	0.09	1.83	4.76	1.03
Education	295	0.03	0.00	0.34	2.37	1.02
Health and social work	4,307	0.48	0.00	0.81	1.79	1.00
Arts, entertain., recreation	17,646	1.98	0.10	1.44	3.41	0.30
Other services	5,424	0.61	0.00	1.07	2.45	0.85
Other sectors	19	0.00	0.00	0.00	0.00	0.00
Missing sector info	182,526	20.49	0.53	1.42	2.84	0.58

Note: Observations are at the quarter – firm level, from the period 2020–2023.

Table A3
Logistic regression estimates using unfiltered default event as response variable

	Default event – unfiltered				
	(1)	(2)	(3)	(4)	(5)
RE	-1.304***	-1.159***	-0.865***	-0.563**	-0.606**
	(0.230)	(0.231)	(0.262)	(0.256)	(0.280)
EM	-1.212***	-1.026***	-1.043***	-0.749***	-0.615***
	(0.111)	(0.111)	(0.112)	(0.113)	(0.132)
Leasing dummy				-0.423***	-0.306***
				(0.033)	(0.041)
Sales growth rate					0.022***
					(0.007)
Liquidity					-0.035***
					(0.007)
Leverage					0.741***
					(0.065)
ROA (after tax)					-0.881***
					(0.046)
EBITDA-to-equity ratio					-0.190***
					(0.028)
Sales-to-assets					-0.108***
					(0.011)
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	890,872	890,872	890,872	890,872	618,916
Akaike Inf. Crit.	106,169.20	100,786.60	100,147.70	94,144.35	53,564.51

*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, logarithmised collateral value, logarithmised loan amount, loan denominated in foreign exchange indication, loan denominated in HUF indication and subsidised 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-owned 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
Logistic regression estimates also including renewable energy firms outside GPCR

	(1)	(2)	(3)	(4)	(5)
All RE	-0.803***	-0.991***	-0.373**	-0.476***	-0.550***
	(0.167)	(0.168)	(0.181)	(0.183)	(0.202)
EM	-1.062***	-1.131***	-1.125***	-0.930***	-0.828***
	(0.124)	(0.124)	(0.124)	(0.125)	(0.149)
Leasing dummy				-0.325***	-0.191***
				(0.034)	(0.043)
Sales growth rate					0.011
					(0.009)
Liquidity					-0.035***
					(0.008)
Leverage					0.875***
					(0.074)
ROA (after tax)					-1.123***
					(0.051)
EBITDA-to-equity ratio					-0.191***
					(0.030)
Sales-to-assets					-0.085***
					(0.013)
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	890,872	890,872	890,872	890,872	618,916
Akaike Inf. Crit.	78,814.55	77,451.80	77,044.62	75,791.09	46,033.80

*Note: Winners of renewable energy auctions are also included in the GPCR and other RE variable. Credit-related controls include longest elapsed loan term and remaining maturity, existing floating rate loan indication, logarithmised collateral value, logarithmised loan amount, loan denominated in foreign exchange indication, loan denominated in HUF indication and subsidised 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 A5
Survival analysis results also including renewable energy firms outside GPCR

	(1)	(2)	(3)	(4)	(5)
All RE	-0.852***	-1.021***	-0.397*	-0.530**	-0.679***
	(0.183)	(0.190)	(0.206)	(0.207)	(0.227)
EM	-0.973***	-1.011***	-1.009***	-0.905***	-0.878***
	(0.131)	(0.132)	(0.133)	(0.133)	(0.150)
Leasing dummy				-0.249***	-0.182***
				(0.038)	(0.043)
Sales growth rate					0.033***
					(0.007)
Liquidity					-0.014*
					(0.008)
Leverage					0.925***
					(0.076)
ROA (after tax)					-0.708***
					(0.066)
EBITDA-to-equity ratio					-0.167***
					(0.033)
Sales-to-assets					0.020*
					(0.011)
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	877,178	776,207	776,207	776,207	575,025

*Note: Winners of renewable energy auctions are also included in the GPCR and other RE variable. Credit-related controls include existing floating rate loan indication, logarithmised collateral value, logarithmised loan amount, loan denominated in foreign exchange indication, loan denominated in HUF indication and subsidised 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 A6
Logistic regression results for firm size categories

		(1)	(2)	(3)	(4)	(5)
Micro (562,476 obs.)	RE (3,567 obs.)	-1.290***	-1.662***	-0.934*	-1.107**	-0.946*
		-0.354	(0.355)	(0.405)	(0.412)	(0.445)
	EM (15,237 obs.)	-1.246***	-1.286***	-1.269***	-1.018***	-1.027***
		(0.167)	(0.167)	(0.168)	(0.169)	(0.222)
Non micro (328,396 obs.)	RE (2,754 obs.)	-0.993**	-1.317***	-0.602	-0.648	-0.546
		(0.379)	-0.38	(0.382)	(0.384)	(0.386)
	EM (15,237 obs.)	-0.777***	-0.886***	-0.916***	-0.826***	-0.648**
		(0.184)	(0.184)	(0.185)	(0.187)	(0.203)
	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

*Note: The upper part of the table shows estimates for the micro firms, middle of the table shows estimates for non-micro firms. Number of observations are shown in parentheses for the whole sample and the variables. Credit-related controls include longest elapsed loan term and remaining maturity, existing floating rate loan indication, logarithmised collateral value, logarithmised loan amount, loan denominated in foreign exchange indication, loan denominated in HUF indication and subsidised loan indications (NHP and Szechenyi). Firm-related controls are age (categories with 5-year buckets), 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).*

Table A7
Logistic regressions on winners of feed-in tariff auctions

	Winners of feed-in tariff auctions		
	(1)	(2)	(3)
Firm age	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)
Micro firm	-0.184**	-0.62***	-0.306***
	(0.072)	(0.084)	(0.09)
Small firm	0.469***	0.097	0.193**
	(0.075)	(0.086)	(0.089)
Medium firm	1.051***	0.64***	0.491***
	(0.08)	(0.09)	(0.092)
Foreign	-1.256***	-1.278***	-1.323***
	(0.145)	(0.146)	(0.147)
Sales growth rate		0.004	-0.004
		(0.008)	(0.008)
Liquidity		-0.025***	-0.019**
		(0.008)	(0.008)
Leverage		0.985***	0.762***
		(0.091)	(0.092)
ROA (after tax)		0.767***	0.639***
		(0.161)	(0.162)
EBITDA-to-equity ratio		0.032	0.031
		(0.038)	(0.038)
Sales-to-assets		-1.122***	-1.054***
		(0.033)	(0.033)
Log of instrumentum size			0.153***
			(0.013)
Log of collateral value			0.026***
			(0.005)
Observations	890,872	618,916	618,916

*Note: The table presents the results for winners of feed-in tariff auctions determinant model. 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).*

MNB WORKING PAPERS 2

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