Journal of Climate Finance 16 (2026) 100092

Contents lists available at ScienceDirect

Journal of Climate Finance

journal homepage: www.journals.elsevier.com/journal-of-climate-finance

Green firms and default risk: Results from a preferential capital requirement programme

Bálint Várgedő [a,b,*], Csaba Burger [c], Donát Kim [a]

[a] Sustainable Finance Department, Central Bank of Hungary, Krisztina körút 55, Budapest 1013, Hungary
[b] Institute of Finance, Corvinus University of Budapest, Fővám tér 8, Budapest 1093, Hungary
[c] Applied Research and Stress Testing Department, Central Bank of Hungary, Krisztina körút 55, Budapest 1013, Hungary

ARTICLE INFO

JEL classifications:
E58
G21
G33
O16

Keywords:
sustainable finance
financial stability
capital requirement
green finance
default probability
green transition
central bank mandates

ABSTRACT

This study evaluates the credit risk of green firms in a preferential capital requirement programme. We utilise loan-level data from a uniquely implemented, taxonomy-based programme from Hungary, applying logistic regressions and survival analysis techniques. We observe significantly reduced credit risk for green firms, even after controlling for a broad set of observed borrower, loan, sector, and time characteristics. Firms with renewable energy and electromobility loans exhibit 1.5 and 1.7 percentage points lower yearly probability of default respectively in the covered period. Models incorporating green characteristics predict a substantially lower credit risk for green firms compared to models excluding green characteristics. These results are economically significant and robust to model specifications including bank-time fixed effects, alternative definitions of green firms and varying default definitions. Our estimates imply that green firms' lower probability of default can potentially rationalize a reduction of several percentage points in capital requirements.

1. Introduction

Climate change has emerged as a primary concern for both central banks and supervisory authorities. Some authors have emphasised that promoting sustainable finance may be considered a legal obligation for central banks, as more than half of them have direct or indirect sustainability mandates (Dikau & Volz, 2021). Others have argued that central banks should avoid unintended trade-offs between climate policy and their core mandates (Diluiso et al., 2021). Several policy actions have been recommended, such as quantitative easing programmes (Dafermos et al., 2018), or the introduction of green macroprudential policy tools (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 for exposures that qualify as green exposures. Such capital requirement 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. The hypothesis of lower risk of green firms is based on their lower level of transition risks, the better financial performance and improved creditworthiness of ESG firms (Brogi & Lagasio, 2018; Carbone et al., 2021). Although the debate about introducing such green tools to the microprudential framework started several years ago (Demekas & Grippa, 2022; Gruenewald et al., 2024), 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) firms and electromobility (EM) firms, using granular, loan-level data from the credit registry, complemented with balance sheet information of these firms. The analysis focuses on the period between 2020 and 2024. We investigate default risk using logistic regression-based default probability (PD)

* Corresponding author at: Sustainable Finance Department, Central Bank of Hungary, Krisztina körút 55, Budapest 1013, Hungary.
E-mail addresses: vargedob@mnb.hu (B. Várgedő), burgercs@mnb.hu (C. Burger), kimdo@mnb.hu (D. Kim).

https://doi.org/10.1016/j.jclimf.2026.100092
Received 8 January 2026; Received in revised form 3 July 2026; Accepted 11 July 2026
Available online 13 July 2026

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 to grasp the magnitude of a fair discount.

Our findings confirm that renewable energy and electromobility firms under the MNB's green preferential capital requirement programme exhibit lower probability of default values compared to their peers during the sample period. Even after controlling for observed risk factors, economic activity and bank screening effects, the dummy of green firms significantly reduces default risk 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. The empirical PD difference can potentially explain several percentage points and around half of the capital requirement discount. This means that the GPCR in its actual form is an active central bank support to catalyse the transition process, and it should be monitored 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). Similarly, enhancing the environmental performance of wholesale and retail banks can mitigate their default risk (Palmieri et al., 2024). 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 green supervisory measures and their effects. Miguel et al. (2024) reports on the inclusion of environmental risks in the ICAAP regulation of large banks in Brazil in 2017, 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. However, smaller banks, exempted from the regulation, expanded their credit supply to these. The measure only impacts moderately the real economy and greenhouse gas emissions. Others have focused on the theoretical modelling of green microprudential measures. Implementing GSF or DPF slows climate change and thus limits physical risk increases, while a GSF may increase bank leverage, potentially posing risks to financial stability (Dafermos & Nikolaidi, 2021). 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 and 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. However, despite these contributions, there remains little empirical evidence from actual GSF programs at the loan level, particularly in the corporate segment.

Our research makes three main contributions to literature on empirical risk differential for green firms. Firstly, we can estimate our results based on ex ante and supervised measures of greenness, relying on a predefined taxonomy issued by the Central Bank of Hungary (see more on this below). Financial institutions flagged and reported the loans in real time, from their issuance onwards, and the reported data were supervised continuously by the central bank. Banks are required to document and store all the necessary evidence regarding the sustainability of the loan, and supervisors assess the eligibility of the loan contracts at each annual review process based on the provided credit documentation. Secondly, banks reported loans that are compliant with the taxonomy of 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. 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. Our results provide empirical support for a risk-based GSF, especially in countries where similar policy measures are in place to support sustainable activities such as subsidised feed-in tariffs in Hungary for renewable energy generation. 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,[4] 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 & 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 for sustainable corporate and municipal financing. The programme initially covered loans and bonds funding renewable energy assets and green bonds only, but in August 2021 the list of eligible activities was substantially expanded to include electromobility, commercial real estate and energy efficiency projects. Qualifying loans must meet one of these financing objectives and have an origination date after 1 January 2020. Eligibility criteria for each of

[4] 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).

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 modernisation of energy-efficient residential buildings, in accordance with the EU Taxonomy.

This capital discount functions as a GSF, allowing banks to deduct it from their Pillar II capital requirements. The discount ranges from 5 to 7% 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% of the institutions' total risk weighted assets. The programme is voluntary, 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% of all banks joined the programme. Exposures covered by the programme have been growing steadily, from 0.8% of NFC exposures (around EUR 225 million) in December 2020 to 4.6% (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, 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 gives the magnitude of 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% of the loans. The reason for missing financial information is threefold. First, the first group of debtors without financial statements were sole entrepreneurs. Second, some small companies where the share of personnel costs is sizeable are eligible for simplified taxation rules (such as the 'KIVA' taxation with reduced employee social contributions). Finally, we did not obtain financials on foreign firms taking out loans from Hungarian banks. 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 where delinquency is unlikely to signal fundamental credit risk event, a minimum of 10% of a firm's outstanding principle had to be in default, as per Banai et al. (2016)[8]. By introducing this threshold, we managed to exclude a substantial amount of technical defaults, as the share of default events drops from 1.1% to 0.8%. As a robustness test, we also examine unfiltered default events as a response variable in one of our model specification sets.

Explanatory variables include credit-related, firm-level financial data, and macroeconomic information. 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[9]) of firm location and whether over 50% 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 & Saunders, 1997; Neagu et al., 2024) and Hungarian credit risk literature (Banai et al., 2016; Burger, 2025). The primary variables 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. Additional variable of interest is an indicator on all RE firms that are not necessarily present in the GPCR, and time varying green indicators on GPCR RE and EM.

For credit-related information missing data points are not present, for firm-level information such as firm size, we introduce 'missing' as a separate category. Such missing data points - apart from balance sheet information described above - are rare, less than 1% of the sample.

[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 % of the portfolio) were still participating in the moratorium (Dancsik & 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.

[8] Formally, firm-level default of firm f at time t (D_{ft}) depends on the loan-level default indicator (D_{ftl}) and exposure amount ($Exposure_{ftl}$):

$$D_{ft} = \begin{cases} if \sum_l D_{ftl} Exposure_{ftl} > 0.1 * \sum_l Exposure_{ftl} then 1 \\ if \sum_l D_{ftl} Exposure_{ftl} \leq 0.1 * \sum_l Exposure_{ftl} then 0 \end{cases}$$

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

Controlling for missing data refers to this procedure in the regression tables.

Table 1 reveals that 0.7% of the observations (6720 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% 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% of observations (24,713 instances), substantially lower than the 32.6-percent share held by firms with leasing loans. See Table A2 in the Appendix for more statistics across sectors.

4. Methodology

We apply two econometric techniques to evaluate the information about 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, 2002) 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 et al., 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:

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

The coefficients (betas) are obtained via maximum likelihood estimation, using the iteratively reweighted least squares method. The same firm appears repeatedly over time in the panel data, so we report the firm-clustered standard errors of coefficients to account for within firm residual correlation. 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).

Loan origination and risk management practices can vary across banks which could in theory bias our coefficients of interest, to tackle this limitation we also estimate model specifications using bank-time fixed effects. Via this approach we can also control for banks potentially selecting better-quality clients into the GPCR and for differences in banks' risk appetites and reporting behaviour. We present the results of these models in the Limitations section. Since our green indicator is defined at the firm-level we cannot introduce firm fixed effects into our models.

As further analysis, we estimate our results with time-varying indicators on RE and EM - that switch to 1 at the time of the first green loan origination in the corresponding program and are 0 before. We argue that there should not be any significant difference between time varying and constant firm-level green indicator estimates, as it is not a GPCR treatment that makes firms less risky. GPCR is rather a labelling device to identify taxonomy aligned green firms or firms with such activities. In one hand, if it is the GPCR treatment that makes firms less risky, one would expect stronger estimated differences using the time varying indicators than using the constant ones. On the other hand, time varying indicators eliminates any potential look ahead bias that could be present in case of constant firm-level indicators, as these partly use future loan origination status to explain current default risk. Overall, by reporting both the time varying and the constant variable results, we aim to tackle the issues on GPCR treatment and the bias simultaneously. RE and EM refer to constant firm-level indicators if not specified otherwise.

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, $S(t) = Prob(t < T)$. Since our observation unit is a firm, not a loan, we measure the survival probability from the firm's first loan origination in our sample. Note that time in this case measures the time since the firm's first 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, $h(t)$.

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

.

The hazard function at time t is the probability that the firm 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 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 $\boldsymbol{x_i}$ 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.

$$h(t, \boldsymbol{x_i}(t)) = \exp(\beta' \boldsymbol{x_i}(t)) \bullet h_0(t) \tag{3}$$

.

Each characteristic's coefficient determines the hazard ratio $(\exp(\beta' \boldsymbol{x_i}(t)))$. 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.[10] 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 % 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:

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

[10] 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.

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 (RE)	890 872	0.007	0.084	0	0	0	0	1
GPCR: Electromobility (EM)	890 872	0.028	0.164	0	0	0	0	1
GPCR: RE time varying	890 872	0.005	0.069	0	0	0	0	1
GPCR: EM time varying	890 872	0.012	0.109	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.

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, $R = 0.12 \bullet w + 0.24 \bullet (1 - w)$, where $w = \frac{(1 - \exp(-50 \bullet PD))}{(1 - \exp(-50))}$.
- 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 illustrate the potential fair capital impact of our estimated risk difference. We use the following regulatory values to the formula: (Loss Given Default as 45%, maturity of 2.5 years and correlation coefficients as a function of PD). We do not model the LGD due to its complex nature, but note that 48% of RE observations have a pledged collateral compared to 30% of the whole sample and 20% of EM observations. Although the Hungarian banking sector predominantly relies on the Standardized Approach supplemented by Pillar II measures, we mimic this using the ASRF formula and unconditional risk differences of firms, discussed later. Overall, we do not aim for a precise, normative calibration of a fair discount, only for an illustration on the range of plausible values in the complex environment of capital requirements.

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 2, 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 A3 in Appendix), which shows that self-selection for participation in the programme is unlikely among sustainable firms. Firms with EM loans (Table 2, 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.

5.2. Default probabilities

The observed quarterly default rates for the whole sample are 75 basis points (bps), while they are only 24 bps for RE and 27 bps for EM. Translating these to yearly default rates,[11] we see 2.9% for the whole sample, 1% for RE and 1.1% for EM firms. 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

[11] Assuming independence, Yearly DR = $1 - (1 - \text{Quarterly DR})^4$. This synthetic yearly default rate closely follows the observed, see Fig. 2A in the Appendix.

Table 2
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	1.170***	0.430***	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 instrument 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 (*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$).

Table 3. We estimate several models to obtain more robust results and to isolate the effect of RE and EM on corporate default risk. We estimate these using both firm-level constant and time varying green indicators, the separate model estimations are presented below each other, separated by a double line. 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. Standard errors are clustered at the firm-level.

The RE coefficients indicate that firms in the GPCR programme exhibit a lower probability of default. In the specifications with constant firm-level indicators, coefficient estimates are in the range of −1.44 to −0.7, which corresponds to odds ratios between 24 and 50%. 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 (at least at a 5-percent level) across all models. The RE dummy remains significant but is lower in magnitude after controlling for the economic activity of firms, implying that RE firms are operating in relatively lower credit risk sectors. Even in Model (5), where all variables describing the financial situation of the firm are controlled for, the RE dummy's coefficient is significant at a 5-percent level. Classification performance of Model (5) is sufficient, the area under the ROC curve (AUROC) measure is 72.54%.

Results based on the time-varying RE indicator provide stronger evidence. When RE status switch to 1 only after the origination of the first RE loan, coefficient estimates are larger in absolute value (between approximately −1.9 and −1.1) and remain statistically significant across all model specifications. This pattern suggests that the lower observed risk of renewable energy firms is not driven by look-ahead bias in the constant indicator.

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 quarterly AME metric. Micro and small enterprises are around 20 basis points riskier quarterly compared to large corporates. However, greenness seems to compensate for these other credit risk factors, as AME for RE and EM decreases quarterly 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 estimated models suggest that this effect is statistically significant, at least at a 5-percent level. Coefficient estimates are relatively stable, lying roughly between −1.13 and −0.83 for the constant indicator and between −0.99 and −0.62 for the time-varying indicator. The constant EM dummy's odds ratios are between 32 and 43%, the marginal impact on an average firm's quarterly PD ranges from 43 to 51 bps (1.68–2.02 pps yearly). If we control for firms which are expected to be similar via the leasing loan indicator (Model (4)-(5)), the magnitude of the time-varying EM coefficient declines somewhat but remains significant, indicating that the lower risk of EM firms cannot be explained solely by their association with leasing-type investments. Whether the 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.

Table 3
Logistic regression estimates on green information and corporates' probability of default.

	(1)	(2)	(3)	(4)	(5)
GPCR RE	-1.174^{***}	-1.437^{***}	-0.670^{**}	-0.800^{**}	-0.694^{**}
	(0.289)	(0.293)	(0.326)	(0.327)	(0.325)
GPCR EM	-1.062^{***}	-1.132^{***}	-1.126^{***}	-0.931^{***}	-0.829^{***}
	(0.138)	(0.138)	(0.137)	(0.138)	(0.160)
GPCR RE time varying	-1.531^{***}	-1.875^{***}	-0.977^{**}	-1.111^{**}	-1.065^{**}
	(0.376)	(0.379)	(0.380)	(0.382)	(0.383)
GPCR EM time varying	-0.876^{***}	-0.989^{***}	-0.978^{***}	-0.652^{***}	-0.621^{**}
	(0.177)	(0.177)	(0.177)	(0.179)	(0.228)
Financial state controls	No	No	No	No	Yes
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	887,172	887,172	612,755
Clustering	Firm	Firm	Firm	Firm	Firm

Note: The two model specifications, with constant and time varying green indicators are separated by a double line. Financial state controls include liquidity, leverage, sales-to-assets ratio, rate on assets and sales growth. 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, subsidised loan indications (NHP and Szechenyi) and leasing flag. 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 results do not show that the constant firm-level indicator would introduce look ahead bias to the estimates, as the time-varying estimates are in the same magnitude, somewhat larger, but not significantly. Substantial GPCR treatment effects are also unlikely based on our estimates.

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. Fig. 1 shows that the probability of survival for both RE and EM are consistently and significantly 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.

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 4. 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.

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%, respectively, while our most detailed Model (5) implies a hazard ratio of 47% for RE. This means that the hazard of RE firms is lower compared to similar firms by a value between 44 and 74% – 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%, which corresponds to a decline of hazard in the range of 58.5–64%.

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% of the loan

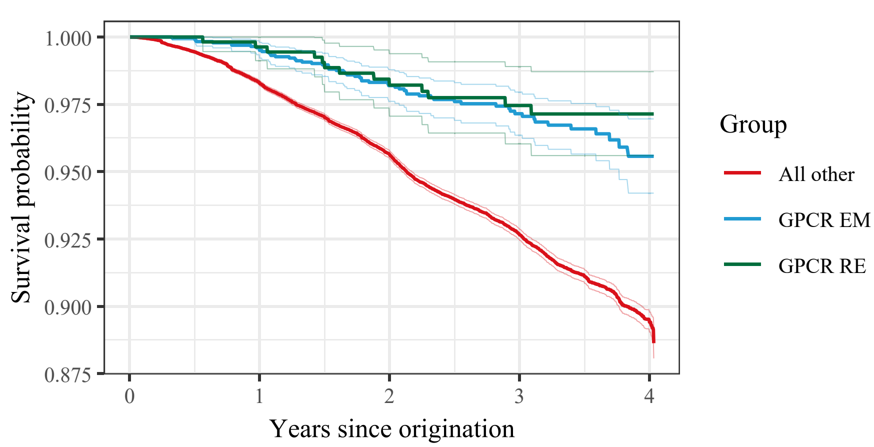

Fig. 1. Kaplan-Meier survival probabilities for RE, EM and other firms. *Note: RE firms' survival probabilities are denoted by green, EM firms' survival probabilities are denoted by blue, all other firms by red. Relative time since loan origination is measured in years in the x-axis. 95th percentile confidence intervals are denoted by corresponding colors.*

Table 4
Survival analysis estimates on green information and 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 ($^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$).

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 A4 and Table A5 illustrate the results of the new two sets of logistic regressions, while Table A6 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, time varying green dummies and all RE used for identification) full logit models (5) are summarised in Table 5. The more inclusive definition of RE firms (All RE) has a significant effect too. The estimated economic relation is similar in magnitude to 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 A6.

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 models (Table A7 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 Fig. 2 for energy and utility firms and in Fig. 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.[14]

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 the BSCs and BS. This design strategy effectively protects the primary structural system from damage during earthquakes of varying intensities and facilitates rapid structural functional recovery after seismic 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 and Lagasio (2018) showed that better ESG performance is associated with higher profitability. EM firms can also signal strong fundamentals and ESG attitude through electromobility purchases (Li et al., 2024). Based on our results, we argue that firms that eventually receive GPCR-eligible

[14] 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.

Table 5
Robustness of logistic regression estimates of the extended models.

	Const green, filt. default	Const green, unfilt. default	Time varying green, filt. def.	GPCR & all RE, filt. default
GPCR RE	−0.695**	−0.606		
	(0.325)	(0.414)		
GPCR EM	−0.829***	−0.615***		−0.828***
	(0.160)	(0.151)		(0.161)
GPCR RE time varying			−1.065**	
			(0.383)	
GPCR EM time varying			−0.621**	
			(0.228)	
GPCR and other RE				−0.550**
				(0.232)
Sales growth rate	0.011	0.022*	0.011	0.011
	(0.010)	(0.009)	(0.010)	(0.010)
Liquidity	−0.035***	−0.035***	−0.036***	−0.035***
	(0.010)	(0.008)	(0.010)	(0.010)
Leverage	0.874***	0.741***	0.878***	0.875***
	(0.092)	(0.081)	(0.092)	(0.092)
ROA (after tax)	−1.112***	−0.881***	−1.121***	−1.123***
	(0.062)	(0.058)	(0.062)	(0.062)
EBITDA-to-equity ratio	−0.191***	−0.190***	−0.195***	−0.191***
	(0.034)	(0.032)	(0.034)	(0.034)
Sales-to-assets	−0.085***	−0.108***	−0.085***	−0.085***
	(0.017)	(0.016)	(0.017)	(0.017)
Credit-related controls	Yes	Yes	Yes	Yes
Economic sector control	Yes	Yes	Yes	Yes
Firm-related controls	Yes	Yes	Yes	Yes
Missing data control	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	618,916	618,916	618,916	618,916
Clustering	Firm	Firm	Firm	Firm

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.[12] 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[13] and flags if the loan was subsidised (NHP and Szechenyi) and leasing flag. 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 (*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$).

loans already differ systematically from other firms by having a subsidized activity or by having strong fundamentals.

5.4. Implications for capital requirement calculation

Finally, as an illustrative example, we look at the potential capital requirement implications of the obtained estimates. First, we show the base capital requirement using the Vasicek (2002) formula introduced earlier. Second, using the risk differential from the logit Model (5), we calculate a range of possible Fair Capital Requirement values for RE and EM firms, both point estimates and a range of likely values using their 1 standard deviation intervals. With a plausible, but conservative value of 5% 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).

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).[15] We also calibrate capital impacts using our less informed logistic PD models, Model (1) and (3), which is more in line with the SA approach. Model (1) compares 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 Fig. 4, using a baseline PD of 5%.[16] Capital impacts in the SA-like approaches are similar or somewhat larger compared to the risk sensitive approach of Model (5).

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 would be justifiable if one assumes that these estimated risk differentials remain, or slightly less if one takes a more conservative approach and uses our lower bound estimates. Note that these estimates are based entirely on historical data and our prudential calibration is simplified and do not consider loss severity heterogeneity or Pillar I and II differences.

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. One could argue that the lower observed risk of green firms is entirely due to the energy price shock of 2022. In other words, it is state-contingent and not caused by structural components. To tackle this concern, we assess the time sensitivity of our results by estimating our usual model specifications using the constant

[15] Most banks use the standardised approach (SA) to calculate capital in Hungary, that is a less risk sensitive approach. For instance, few distinctions are made for SME corporates in the SA method.

[16] 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 Fig. 1A.

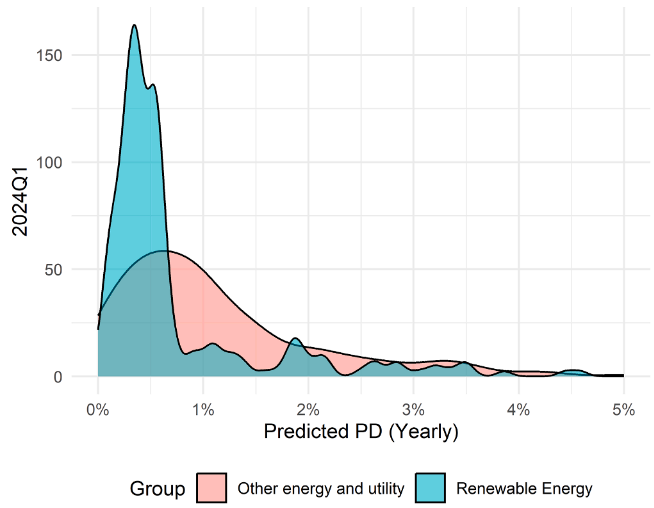

Fig. 2. Predicted PD for energy and utility firms in Q1 2024. Note: Estimations are based on Model (5) for RE firms and other energy firms in the last quarter of the sample (Q1 2024). Default probabilities were converted to yearly values.

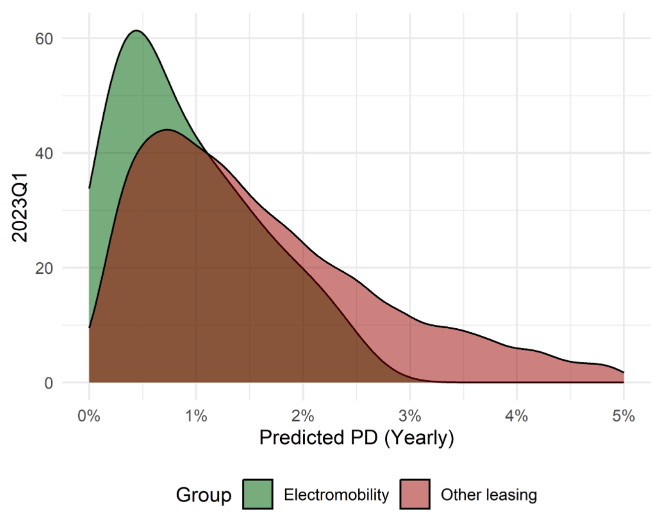

Fig. 3. Predicted PD for electromobility and other firms with leasing loans in Q1 2024. Note: Estimations are based on Model (5) for EM firms and firms with other leasing loans in the last quarter of the sample (Q1 2024). Default probabilities were converted to yearly values.

firm-level green indicators on a pre and a post energy crisis period (before and after 2021 year-end). The results of the subperiod analysis are shown in Table A8. The coefficients are very homogenous across the subperiods and consistently negative in all specifications. Not all coefficients are significant due to fewer observations and higher standard errors, especially for RE. Overall, the lower risk is observed across subperiods which increases the external validity of our results. Additionally, the frequency and intensity of such transition risks may increase along a net-zero pathway, likely widening the risk differential. Conversely, we can not fully establish that the observed risk differential would persist under materially different regulatory, or investor-sentiment regimes, as our sample covers a period with climate-related policy support and investor interest in sustainable activities.

Due to this shorter sample period, we mainly use 1-quarter ahead default events as response variables in our logistic regressions. First, we assess whether synthetic yearly rates based on quarterly default rates are in line with 1-year ahead default events (Fig. 2A). In line with intuition, the two indicators of yearly default rates are very similar, apart from the

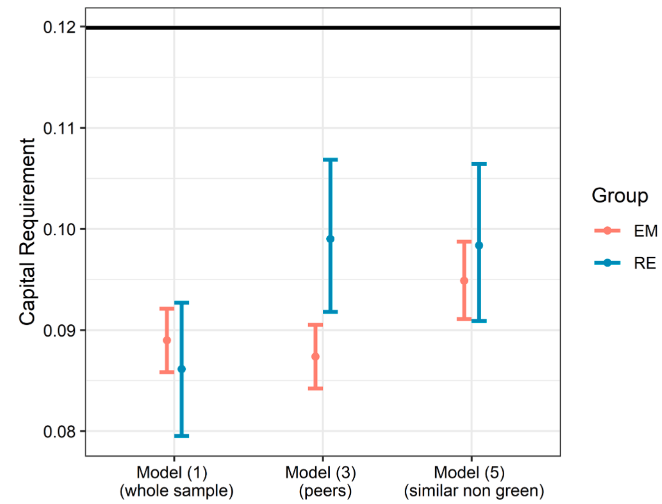

Fig. 4. Fair capital requirements calibration. *Note: Results based on the range of logit Model (1), (3) and (5)'s odds ratios for RE and EM, and their respective confidence intervals. Capital requirements are based on the PD difference between green firms and the whole sample (Model (1)), peer firms (Model (3)) and similar non-green firms (Model (5)). PD is set at 5 % in all cases. Black line represents the baseline capital requirement.*

last 3 quarters, where observed 1-year ahead default rates are downward biased. We estimate our logistic regression set ups using 1-year ahead default events on the sample before 2023Q2, where it can be identified (see Appendix, Table A9). The coefficients are virtually unchanged across model specifications compared to previous results. RE and EM coefficients in Model 5 are significant at the 10 and 1% level, respectively. As a further robustness check, we estimate the probability of default in a 2-year period after origination to reduce sensitivity to short-term fluctuations on the sample firms with loan origination before 2022Q2 (where it can be identified without bias). The estimated coefficients are in line with previous results but are only significant for EM in Model 3–5 (Table A10). Note that the reduced sample period, observations per firm, low number of RE firms and saturated models creates substantially higher standard errors that cause insignificancy of RE in some cases. Default definition does not seem to affect our results materially.

One could be concerned about non-random missingness of balance sheet data across firms. Generally, the balance sheet information are missing for firms in special tax schemes or foreign corporates. Firstly, we estimate our logistic regression set ups on the subsample of observations with missing balance sheet information (Table A11). The ratio of observations with missing balance sheet for the whole sample and RE or EM firms is also around 30%. The estimated coefficients are similar in this subsample to whole sample for EM, but are larger and also insignificant for RE due to higher standard errors. Our previous estimates for the observation with balance sheet data show consistently negative coefficients for RE and EM. Secondly, we perform an inverse probability weighted logit model estimation. We estimate a logit model for the probability that balance sheet variables are observed, using firm characteristics, sector of the firm, RE and EM indicators and time fixed effects. We then construct inverse probability weights for each observation[17] and re-estimate our baseline specification on the fully observed sample weighted by the inverse probabilities. This robustness test enables us to increase the relative weights of observations with balance sheet data but very similar to those without. Both RE and EM coefficients are virtually unchanged, they are also significant at the 10%

[17] As the winsorised ratio of the sample mean probability and the predicted probability of the observation having balance sheet information.

and 1% level, respectively (Table A12). Overall, it is unlikely that missing data distorts our results since both subsamples show similar patterns for our variables of interests.

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. We argue this selection does not bias our estimates for multiple reasons. All our observations are 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. To strengthen this qualitative argument, we perform a quasi-experimental quantitative design element, a propensity score matching. We match the closest firm for each RE and EM firm at the first time they are observed in our sample, based on sector, size, age, and origination quarter. Then we estimate a simple logit model on the reduced, matched panel sample both for RE and EM, where the only explanatory variable is either RE or EM for the corresponding reduced sample. Estimated coefficients based on the matched sample are in line with previous results, somewhat larger for RE (−1.01), and are significant at the 5-percent and 1-percent level, respectively (Table A13). This means that RE and EM firms are less risky than firms really similar to them based on the attributes used during matching.

The second potential selection bias refers to selection and screening effects by banks, or banks different risk appetites. Potentially some banks with superior screening techniques dominate the GPCR program, while others with less developed monitoring practices also underuse the opportunities of this program, hence our estimates biased by the quality of risk management of banks. To address this potential bias, we estimate bank-time fixed effects models where we can control for the risk appetite or credit monitoring practices of each bank. Furthermore, it also controls for risk monitoring developments across origination quarters at each bank. The results of these coefficients estimates are shown in Table A14. They are virtually the same as in our baseline models, implying banks practices are unlikely to influence our results.

Our previous results showing that other RE firms not included in the programme had also lower default risk, suggest that observed risk differential extends beyond program participants. This directly implies that self-selection to the program can not be the only driver of the risk differential, as similar green firms outside program also exhibit lower default rates. It also suggests no selection from the banks' side, as they did not include these firms to 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 of the low risk of green firms).[18] 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 firms in a green capital programme have empirically lower default rates in the covered period. Renewable energy firms compensate for the additional default risk implied by their young age. Additionally, we show that, after controlling for a broad set of borrower and loan characteristics and time fixed effects, renewable energy and electromobility firms still show lower default probabilities. The estimated realized 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, including bank-time fixed effects identification strategies.

Using a simplified capital requirement formula (based on an asymptotic single risk factor model), we illustrate that while uncertainties are substantial in relation to a risk-based capital deduction for green loans, around one half of this discount seems to be justifiable based on our results. Although the capital discount in this framework is generous, a reduction of several percentage points could be reasonable by our estimated empirical risk differences. In jurisdictions with similar state guaranteed subsidy schemes that support renewable energy generation or other sustainable activities, similar preferential treatment of green loans could be calibrated based on our illustrative calculations.

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.

Funding

The project identified by EKOP-KDP-CORVINUS−24–4 was realized with the support of the National Research, Development, and Innovation Fund provided by the Ministry of Culture and Innovation, as part of the University Research Scholarship Program- Cooperative Doctoral Program announced for the 2024/2025 academic year.

CRediT authorship contribution statement

Donát Kim: Validation, Supervision, Resources, Conceptualization. **Csaba Burger:** Writing – review & editing, Validation, Data curation, Conceptualization. **Bálint Várgedő:** Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[18] There are 15 firm-quarter (from 13 firms) observations in our sample which indicate default for GPCR RE firms, 36 for all RE firm-related default observations (from 30 firms). The overall number of GPCR RE and all RE firms are 566 and 1015, respectively.

Acknowledgements

The authors would like to thank Marianna Endrész (discussant) and Pavol Jurča (discussant) for providing valuable feedback. The paper has also benefited from discussions at various conferences: ECB 7th Macroprudential Policy Group Workshop, European Commission JRC 6th Summer School on Sustainable Finance, XII. Hungarian Economic Association Doctoral Workshop Pécs. The views expressed are solely those of the authors and do not necessarily represent the views of the Magyar Nemzeti Bank.

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 % 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	5299	0.60	67.47	0.25	67.96	0.21
Utility	3256	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	4453	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	4307	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	5424	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 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 (*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$).

Table A4
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
	(0.302)	(0.304)	(0.388)	(0.370)	(0.414)
EM	−1.212***	−1.026***	−1.043***	−0.749***	−0.615***
	(0.136)	(0.137)	(0.135)	(0.135)	(0.151)
Sales growth rate					0.022*
					(0.009)
Liquidity					−0.035***
					(0.008)
Leverage					0.741***
					(0.081)
ROA (after tax)					−0.881***
					(0.058)
EBITDA-to-equity ratio					−0.190***
					(0.032)
Sales-to-assets					−0.108***
					(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	890,872	890,872	888,152	888,152	614,114
Clustering	Firm	Firm	Firm	Firm	Firm

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 A5
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*	−0.488*
	(0.196)	(0.200)	(0.224)	(0.228)	(0.231)
EM	−1.062***	−1.131***	−1.125***	−0.930***	−0.800***
	(0.138)	(0.138)	(0.137)	(0.138)	(0.160)
Sales growth rate					0.012
					(0.010)
Liquidity					−0.037***
					(0.010)
Leverage					0.945***
					(0.092)
ROA (after tax)					−1.084***
					(0.060)
EBITDA-to-equity ratio					−0.178***
					(0.034)
Sales-to-assets					−0.086***
					(0.017)
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	887,172	887,172	612,755
Clustering	Firm	Firm	Firm	Firm	Firm

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) and leasing flag. 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
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, subsidised loan indications (NHP and Szechenyi) and leasing flag. 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 A7
Logistic regression results for firm size categories

		(1)	(2)	(3)	(4)	(5)
Micro (562,476 obs.)	RE (3567 obs.)	−1.290***	−1.656***	−0.926*	−1.108***	−0.948*
		(0.352)	(0.356)	(0.414)	(0.425)	(0.423)
	EM (15,237 obs.)	−1.246***	−1.286***	−1.270***	−1.018***	−1.027***
		(0.183)	(0.186)	(0.186)	(0.186)	(0.234)
Non micro (328,396 obs.)	RE (2754 obs.)	−0.993*	−1.162*	−0.538	−0.635	−0.520
		(0.472)	(0.481)	(0.463)	(0.464)	(0.438)
	EM (15,237 obs.)	−0.777***	−0.923***	−0.932***	−0.831***	−0.659**
		(0.210)	(0.201)	(0.198)	(0.200)	(0.214)
	Financial state controls	No	No	No	No	Yes
	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
	Clustering	Firm	Firm	Firm	Firm	Firm

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. Financial state controls include liquidity, leverage, sales-to-assets ratio, rate on assets and sales growth. 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 A8
Pre and post energy shock subsample results

		(1)	(2)	(3)	(4)	(5)
Pre (266,696 obs.)	RE (1874 obs.)	−1.144*	−1.418**	−0.501	−0.628	−0.580
		(0.499)	(0.507)	(0.472)	(0.480)	(0.486)
	EM (6321 obs.)	−0.859***	−0.909***	−0.916***	−0.829**	−0.728*
		(0.261)	(0.261)	(0.261)	(0.263)	(0.289)
Post (624,176 obs.)	RE (4447 obs.)	−1.186***	−1.435***	−0.721	−0.831*	−0.677
		(0.352)	(0.355)	(0.413)	(0.418)	(0.427)
	EM (18,392 obs.)	−1.140***	0.002***	−1.193***	−0.978***	−0.867***
		(0.153)	(1.63e−9)	(0.152)	(0.154)	(0.186)
	Financial state controls	No	No	No	No	Yes
	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
	Clustering	Firm	Firm	Firm	Firm	Firm

Note: The upper part of the table shows estimates for the pre 2022 period, middle of the table shows estimates for the post 2022 period. Number of observations are shown in parentheses for the whole sample and the variables. Financial state controls include liquidity, leverage, sales-to-assets ratio, rate on assets and sales growth. 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 A9
Logistic regression results using 1-year ahead default event as response variable

	Yearly default event				
	(1)	(2)	(3)	(4)	(5)
GPCR RE	−1.108***	−1.392***	−0.534	−0.649*	−0.631**
	(0.294)	(0.299)	(0.327)	(0.327)	(0.317)
GPCR EM	−1.035***	−1.113***	−1.120***	−1.012***	−0.887***
	(0.146)	(0.146)	(0.145)	(0.147)	(0.163)
Sales growth rate					0.025***
					(0.007)

(continued on next page)

Table A9 (*continued*)

	Yearly default event				
Liquidity					−0.016**
					(0.008)
Leverage					1.012***
					(0.085)
ROA (after tax)					−0.900***
					(0.065)
EBITDA-to-equity ratio					−0.173***
					(0.031)
Sales-to-assets					−0.025*
					(0.015)
Quarter FE	No	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes
Firm-related controls	No	Yes	Yes	Yes	Yes
Missing data control	No	Yes	Yes	Yes	Yes
Economic sector control	No	No	Yes	Yes	Yes
Credit-related controls	No	No	No	Yes	Yes
Sample			2020Q1–2023Q2		
Observations	674,177	674,177	670,748	670,748	464,682
Clustering	Firm	Firm	Firm	Firm	Firm

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Note: Response variable is the binary (filtered) default event indicator in the following 1-year period. Hence the sample is shrinked to observations between 2020Q1−2023Q2. Credit-related controls include leasing dummy, 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) and leasing flag. 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 A10

Logistic regression results using 2-year ahead default event at origination

	2-Year ahead default event				
	(1)	(2)	(3)	(4)	(5)
GPCR RE	−0.968*	−1.370**	−0.390	−0.5430	−0.599
	(0.411)	(0.420)	(0.464)	(0.465)	(0.477)
GPCR EM	−1.001***	−1.084***	−1.106***	−0.934***	−0.843***
	(0.215)	(0.217)	(0.218)	(0.220)	(0.248)
Sales growth rate					−0.002**
					(0.001)
Liquidity					0.013
					(0.012)
Leverage					1.218***
					(0.143)
ROA (after tax)					0.110
					(0.180)
EBITDA-to-equity ratio					−0.089
					(0.068)
Sales-to-assets					0.055***
					(0.016)
Quarter FE	No	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes
Firm-related controls	No	Yes	Yes	Yes	Yes
Missing data control	No	Yes	Yes	Yes	Yes
Economic sector control	No	No	Yes	Yes	Yes
Credit-related controls	No	No	No	Yes	Yes
Sample			2020Q1–2022Q2		
Observations	79,242	79,242	78,254	78,254	49,187
Clustering	Firm	Firm	Firm	Firm	Firm

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Note: Response variable is the binary (filtered) default event indicator in the 2-year period after origination. Hence the sample is shrinked to observations between 2020Q1−2022Q2 and one observation per firm. Credit-related controls include leasing dummy, 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) and leasing flag. 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 A11
Logistic results on the subsample of missing balance sheet information

Firms	Observations		Quarterly default event			
with no BS data by GPCR group			(1)	(2)	(3)	(4)
169 out of 680	1030 out of 6321	GPCR RE	−2.365*	−3.065**	−1.656	−1.676
			(1.002)	(1.017)	(1.302)	(1.210)
895 out of 2998	5369 out of 24713	GPCR EM	−1.250***	−1.470***	−1.458***	−1.154***
			(0.279)	(0.279)	(0.278)	(0.279)
Quarter FE			No	Yes	Yes	Yes
County FE			No	Yes	Yes	Yes
Firm-related controls			No	Yes	Yes	Yes
Economic sector control			No	No	Yes	Yes
Credit-related controls			No	No	No	Yes
Sample			No balance sheet information			
Clustering			Firm	Firm	Firm	Firm
Observations			254,309	254,309	254,309	254,309

*p < 0.1; **p < 0.05; ***p < 0.01.
Note: The sample is the observations without balance sheet information. The left side of the table indicates the number of firms and quarterly observations of these in the sample by GPCR indicator (for example out of the 6321 RE observations 1030 have missing balance sheet data).

Table A12
Logistic results using financial variables with inverse probability weighting

	(5)
GPCR RE	−0.654*
	(0.328)
GPCR EM	−0.789***
	(0.171)
Sales growth rate	0.015
	(0.010)
Liquidity	−0.034***
	(0.010)
Leverage	0.902***
	(0.096)
ROA (after tax)	−1.00***
	(0.064)
EBITDA-to-equity ratio	−0.189***
	(0.035)
Sales-to-assets	−0.068***
	(0.018)
Quarter FE	Yes
County FE	Yes
Firm-related controls	Yes
Missing data control	Yes
Economic sector control	Yes
Credit-related controls	Yes
Bank x Orig. Time FE	No
Observations	600,200
Clustering	Firm
Note: *p < 0.1; **p < 0.05; ***p < 0.01	

Table shows usual model (5) estimates inversely weighted by the probability that balance sheet variables are observed, using a logit model on Firm-related controls, Economic sector of the firm, RE and EM indicators and Quarter fixed effects to estimate probabilities. Inverse probability weights are winsorised.

Table A13
Logistic results using propensity score matching

	(1)		(2)	
GPCR RE	−1.007**			
	(0.366)			
GPCR EM			−0.921***	
			(0.169)	
Observations	10,802		46,410	
Clustering	Firm		Firm	
			Max Std. Mean Diff.	
Variable Group	RE-All firms	RE-Matched	EM-All firms	EM-Matched
Propensity distance	1053	0,454	0,598	0,000
Firm age	−0,634	−0,502	−0,007	0,003
Size (ordered)	0,267	−0,061	−0,289	0,054
Orig. date	−0,370	−0,416	0,426	−0,015
NACE lvl2	1156	0,164	0,130	0,042
NACE lvl3	1156	0,164	0,130	0,042

Table shows estimates on a matched sample of firms for RE and EM. Propensity score matching is performed at the first time a firm is observed based on sector (both NACE lvl 2 and 3), size, age, and origination quarter. Standardized mean differences are reported below the regression results for each matched sample. For categorical variables (origination quarter, NACE lvl 2 and 3), the maximum value of std. mean diff. is reported across the dummy group. In the first line of max std. mean diff. the propensity score distances of the samples are reported.

Table A14
Bank-Origination quarter fixed effects models

Default event					
	(1)	(2)	(3)	(4)	(5)
GPCR RE	−1.067***	−1.320***	−0.594	−0.731*	−0.672*
	(0.290)	(0.295)	(0.331)	(0.333)	(0.336)
GPCR EM	−0.963***	−1.031***	−1.033***	−0.907***	−0.799***
	(0.139)	(0.139)	(0.138)	(0.139)	(0.163)
Sales growth rate					0.012
					(0.010)
Liquidity					−0.033***
					(0.009)
Leverage					0.841***
					(0.092)
ROA (after tax)					−1.122***
					(0.062)
EBITDA-to-equity ratio					−0.194***
					(0.035)
Sales-to-assets					−0.082***
					(0.018)
Quarter FE	No	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes
Firm-related controls	No	Yes	Yes	Yes	Yes
Missing data control	No	Yes	Yes	Yes	Yes
Economic sector control	No	No	Yes	Yes	Yes
Credit-related controls	No	No	No	No	Yes
Bank x Orig. Time FE	Yes	Yes	Yes	Yes	Yes
Observations	879,416	879,416	875,899	875,899	600,200
Clustering	Firm	Firm	Firm	Firm	Firm

Note: Credit-related controls include leasing dummy, 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) and leasing flag. 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 (*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$).

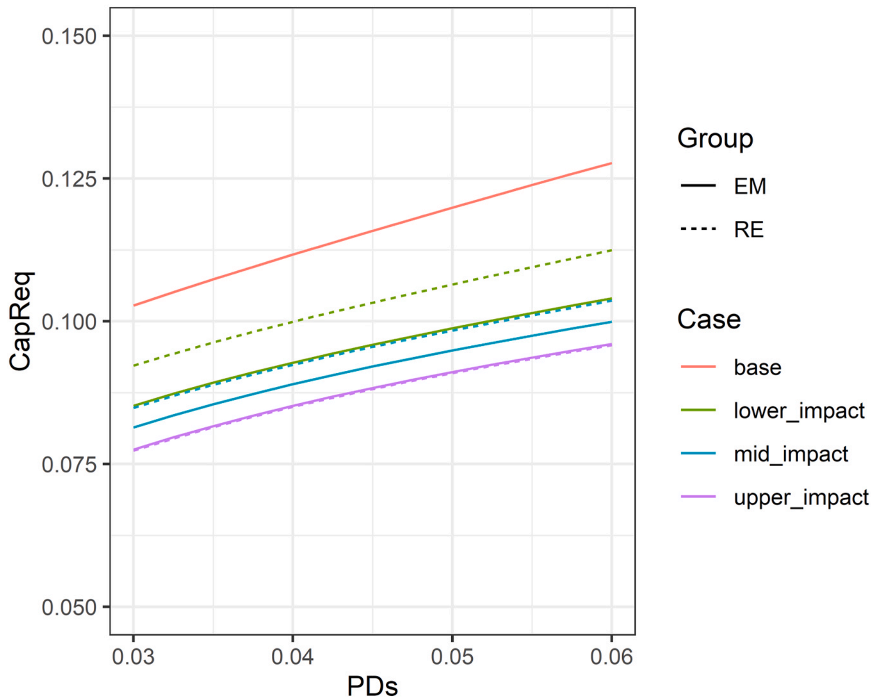

Fig. 1A. Fair capital requirements for the corporate segment as a function of PD. Note: Results based on the range of logit Model (5)'s odds ratios, a lower bound of 66.8 and an upper bound of 37.3 % for RE firms and a lower bound of 50.7 and an upper bound of 37.5 % for EM firms. Dotted line represents fair capital requirements for RE, solid lines for EM

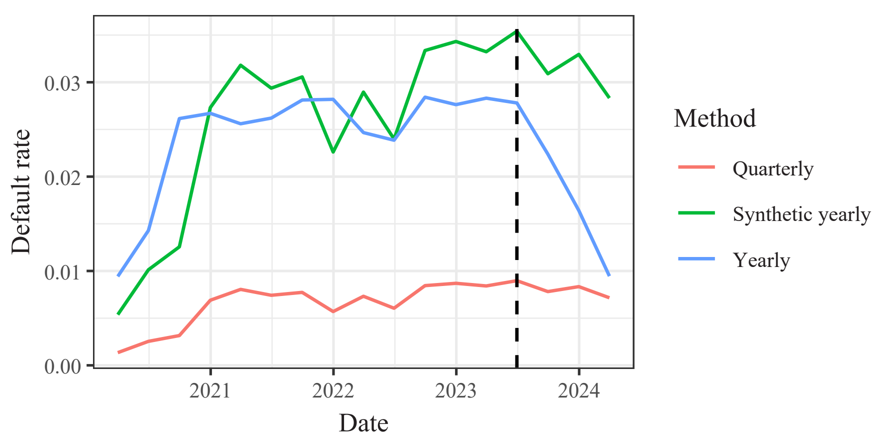

Fig. 2A. Default rates. Note: The calculation is as follows: Synthetic $Yearly\ DR = 1 - (1 - Quarterly\ DR)^4$

References

Altman, E., & Saunders, A. (1997). Credit risk measurement: Developments over the last 20 years. *Journal of Banking & Finance, 21*(11-12), 1721–1742. https://doi.org/10.1016/S0378-4266(97)00036-8

Banai, Á., Körmendi, G., Lang, P. & Vágó, N. (2016). Modelling the credit risk of the Hungarian SME sector. MNB Occasional Papers, No. 123, Magyar Nemzeti Bank, Budapest.

Bank of England (2021). Climate-related financial risk management and the role of capital requirements. Climate Change Adaption Report.

Berlinger, E., Keresztúri, J. L., Lublóy, Á., & Vőneki, Z. T. (2021). Does governance matter? Country-level determinants of operational risk. *Society and Economy, 43*(4), 289–313. https://doi.org/10.1556/204.2021.00018

Billio, M., Costola, M., Pelizzon, L., & Riedel, M. (2022). Buildings' Energy Efficiency and the Probability of Mortgage Default: The Dutch Case. *The Journal of Real Estate Finance and Economics, 65*, 419–450. https://doi.org/10.1007/s11146-021-09838-0

Brogi, M., & Lagasio, V. (2018). Environmental, social, and governance and company profitability: Are financial intermediaries different? *Corporate Social Responsibility and Environmental Management, 26*(3), 576–587. https://doi.org/10.1002/csr.1704

Burger, C. (2011). Adoption patterns of occupational pensions in Germany. *Environment and Planning A, 43*(11), 2666–2687. https://doi.org/10.1068/a4455

Burger, C. (2025). Defaulting alone: SME owner numbers and credit risk in Hungary. *Journal of Small Business Management*, 1–27. https://doi.org/10.1080/00472778.2025.2502090

Burger, C., & Wójcik, D. (2024). The Geography of Climate Change Risk Analysis at Central Banks in Europe. *GeoJournal, 89*, 213. https://doi.org/10.1007/s10708-024-11174-8

Campiglio, E. (2016). Beyond carbon pricing: The role of banking and monetary policy in financing the transition to a low-carbon economy. *Ecological Economics, 121*, 220–230. https://doi.org/10.1016/j.ecolecon.2015.03.020

Carbone, S., Giuzio, Kapadia, S., Kramer, J. S., Nyholm, K., & Vozian, K. (2021). The low-carbon transition, climate commitments and firm credit risk. *ECB WP (No 2631).* https://doi.org/10.2139/ssrn.3991358

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society Series B (Methodological), 34*, 187–220. https://doi.org/10.1111/j.2517-6161.1972.tb00899.x

Dafermos, Y., & Nikolaidi, M. (2021). How can green differentiated capital requirements affect climate risks? A dynamic macrofinancial analysis. *Journal of Financial Stability, 54*. https://doi.org/10.1016/j.jfs.2021.100871

Dafermos, Y., Nikolaidi, M., & Galanis, G. (2018). Climate Change, Financial Stability and Monetary Policy. *Ecological Economics, 152*, 219–234. https://doi.org/10.1016/j.ecolecon.2018.05.011

Dancsik, B., & Fellner, Z. (2021). Why do households participate in the loan moratorium in Hungary? Theoretical and empirical considerations. *Acta Oeconomica, 71*(S1), 119–140. https://doi.org/10.1556/032.2021.00032

Demekas, D., & Grippa, P. (2022). Walking a Tightrope: Financial Regulation, Climate Change, and the Transition to a Low-Carbon Economy. *Journal of Financial Regulation, 8*(2), 203–229. https://doi.org/10.1093/jfr/fjac010

Dikau, S., & Volz, U. (2021). Central bank mandates, sustainability objectives and the promotion of green finance. *Ecological Economics, 184*. https://doi.org/10.1016/j.ecolecon.2021.107022

Diluiso, F., Annicchiarico, B., Kalkuhl, M., & Minx, J. C. (2021). Climate actions and macro-financial stability: The role of central banks. *Journal of Environmental Economics and Management, 110*. https://doi.org/10.1016/j.jeem.2021.102548

Dunz, N., Naqvi, A., & Monasterolo, I. (2021). Climate sentiments, transition risk, and financial stability in a stock-flow consistent model. *Journal of Financial Stability, 54*. https://doi.org/10.1016/j.jfs.2021.100872

Fraisse, H., Lé, M., & Thesmar, D. (2020). The real effects of bank capital requirements. *Management Science, 66*, 5–23. https://doi.org/10.1287/mnsc.2018.3222

Gropp, R., Mosk, T., & Ongena, S. (2019). Banks response to higher capital requirements: Evidence from a quasi-natural experiment. *Review of Financial Studies, 21*(1), 266–299. https://doi.org/10.1093/rfs/hhy052

Gruenewald, S., Knijp, G., Schoenmaker, D., & van Tilburg, R. (2024). Embracing the Brave New World: A Response to Demekas and Grippa. *Journal of Financial Regulation, 10*(1), 127–134. https://doi.org/10.1093/jfr/fjad011

Guin, B. & Korhonen, P. (2020). Does Energy Efficiency Predict Mortgage Performance? Bank of England Working Paper No. 852, https://doi.org/10.2139/ssrn.3532373.

Lamperti, F., Bosetti, V., Roventini, A., Tavoni, M., & Treibich, T. (2021). Three green financial policies to address climate risks. *Journal of Financial Stability, 54*. https://doi.org/10.1016/j.jfs.2021.100875

Li, W., Padmanabhan, P., & Huang, C. (2024). ESG and debt structure: Is the nature of this relationship nonlinear? *International Review of Financial Analysis, 91*, Article 103027. https://doi.org/10.1016/j.irfa.2023.103027

Mathew, P., Issler, P., & Wallace, N. (2021). Should commercial mortgage lenders care about energy efficiency? Lessons from a pilot study. *Energy Policy, 150*. https://doi.org/10.1016/j.enpol.2021.112137

MNB (2019). MNB Green Programme. Accessed (2024.02.29.): https://www.mnb.hu/greenfinance/english.

MNB (2021). Sustainability and central bank policy – Green aspects of the Magyar Nemzeti Bank's monetary policy toolkit. Magyar Nemzeti Bank. Assessed (2024.02.29.): https://www.mnb.hu/letoltes/ sustainability-and-central-bank-policy-green-aspects-of-the-magyar-nemzeti-bank-smonetary-policy-toolkit.pdf.

Miguel, F., Pedraza, A., & Ruiz-Ortega, C. (2024). Climate Change Regulations: Bank Lending and Real Effects. *Journal of Financial Stability, 70*. https://doi.org/10.1016/j.jfs.2023.101212

Mueller, I., & Sfrappini, E. (2022). Climate change-related regulatory risks and bank lending. *ECB Working Paper, No. 2670*. Frankfurt a. M: European Central Bank (ECB). https://doi.org/10.2866/617645

Neagu, F., Tatarici, L., Dragu, F., & Stamate, A. (2024). Are green loans less risky? Micro-evidence from a European Emerging Economy. *Journal of Financial Stability, 70*. https://doi.org/10.1016/j.jfs.2023.101208

Oehmke, M., & Opp, M. (2022). Green Capital Requirements. *Swedish House of Finance Research Paper No 22-16*. https://doi.org/10.2139/ssrn.4040098

Palmieri, E., Ferilli, G. B., Altunbas, Y., Stefanelli, V., & Geretto, E. F. (2024). Business model and ESG pillars: The impacts on banking default risk. *International Review of Financial Analysis, 91*. https://doi.org/10.1016/j.irfa.2023.102978

Parker, S., Peters, G. F., & Turetsky, H. F. (2002). Corporate governance and corporate failure: a survival analysis. *Corporate Governance, 2*, 4–12. https://doi.org/10.1108/14720700210430298

Stepanova, M., & Thomas, L. (2002). Survival Analysis Methods for Personal Loan Data. *Operations Research, 50*, 277–289. https://doi.org/10.1287/opre.50.2.277.426

Umar, M., Ji, X., Mirza, N., & Naqvi, B. (2021). Carbon neutrality, bank lending, and credit risk: Evidence from the Eurozone. *Journal of Environmental Management, 296*. https://doi.org/10.1016/j.jenvman.2021.113156

van der Net, J., Janssens, A., Eijkemans, M., et al. (2008). Cox proportional hazards models have more statistical power than logistic regression models in cross-sectional genetic association studies. *European Journal of Human Genetics, 16*, 1111–1116. https://doi.org/10.1038/ejhg.2008.59

Vasicek, O. A. (2002). The Distribution of Loan Portfolio Value. *Risk, 15*(12).

Yameen, J., Kijkasiwat, P., Hussain, A., et al. (2024). Green finance in banking industry: a systematic literature review. *SN Business Econ, 4*(2024), 91. https://doi.org/10.1007/s43546-024-00683-w