**Are green loans less risky? Micro-evidence from an European Emerging Economy***

Florin Dragu [a,b], Florian Neagu [a,b], Amalia Stamate[b], Luminita Tatarici[b]

**Abstract:**

We investigate if green loans granted by banks bear less credit risk compared with non-green loans. We also explore if firms with sounder financial profile are more prone to have access to green loans. Using a novel micro database covering all green loans granted by Romanian banks over the period 2010-2020 and individual financial statements of debtors, we find that probability of default is 10 percent lower for companies with green loans compared with the rest of companies financed by banks. We also discuss possible policy implications from these findings.

**Keywords**: financial stability, macroprudential policy, corporate lending, credit risk, green loans, micro data

**JEL Classification: C31, G32, E58, G21, G28**

[a,b] Bucharest University of Economic Studies, National Bank of Romania, e-mail: Florin.Dragu@bnro.ro

[b] National Bank of Romania

* The opinions expressed in this paper are those of the authors and do not necessarily represent the views of the National Bank of Romania or Bucharest University of Economic Studies. We would like to thank Balázs Markó for his role as a research analyst in conducting this study. We would also like to express our gratitude to the participants in the 15th South-Eastern European Economic Research Workshop, organized by Bank of Albania in December 2021, for their useful comments.

## 1. Introduction

There is a broad agreement that finance should play an active role in fostering green transition (Park and Kim, 2020). Investors and governments are searching to increase green finance, while banks and other creditors are encouraged to expand their green exposures. In such circumstances, a key question is about the level of credit risk from green finance compared with non-green portfolios. From a policy perspective, this question is even more important for those authorities planning to allow lower capital charges for banks green exposures. The National Bank of Hungary has already implemented lower Pillar 2 requirements for green loans[2], while the European Commission (EC) investigates potential solutions for lower risk weights for computing Pillar 1 capital charges (European Commission, 2021). Inadequate prudential buffers may impair banks' ability to cope with negative credit risk shocks. Currently, this risk is subdued due to relatively small share of green loans in banks portfolio (for example, the EU average is around 8 percent of total loans granted to firms at December 2019, European Banking Authority, 2021), but the tendency is towards important increase of these exposures.

Our paper tries to touch upon three topics. First, we investigate the credit risk of green bank loans compared with loans than are not registered as green exposures. We evaluate the hyphothesis that companies with green loans generate a lower credit risk, considering green investments as means for decarbonization with a positive impact on their financial stance. We compute the probability of default for green loans versus non-green loans and observe that the former are less risky (on average by 10 percent). We control for the endogeneity using an average treatment effects model, with several types of estimators. This outcome underpins authorities' initiatives to release capital charges against green exposures in order to foster this type of financing in a sustainable way. Finally, we debate on the more appropriate regulatory approach, taking into account the long-term horizon specific to transition measures and potential regulatory changes, and conclude that microprudential authorities are better equipped to reach this purpose.

Second, we examine the profile of firms with green loans, assessing whether sounder firms are more prone to contract this type of loans for greening their activities. We discover that solid financial management is a relevant factor in explaining company' access to green lending.

[2] https://www.mnb.hu/letoltes/green-retail-lending-in-hungary.pdf

Companies with upper profit margin and lower degree of indebtedness are more likely to take such loans, with higher probability for firms in agriculture and utilities sectors.

Third, climate change agenda implies policies spanning on decades. For example, several measures already envisaged at the international level look at year 2050 as benchmark for targeting lower $CO_2$ emissions. However, as real life highlighted multiple times, authorities often change rules during the game. A relevant question is whether companies involved in supporting climate change agenda are able to manage such potential negative behavior of the authorities. We observe that such developments have consequences for firms acting in renewable energy in terms of credit risk, their repayment capacity deteriorating considerably when authorities amend the legal framework in short notice. We learn that fostering green finance without major negative consequences on credit risk requires higher predictability regarding government's decisions on climate change agenda.

Another important novelty of our paper refers to the database that we use to run the analyses. We employ a new micro database, covering all green loans financed by the largest banks in the system (their market share is 86 percent of total assets), during 2010-2020. The majority of studies use either loan information from banks' corporate sustainability reports (Song et al., 2019; Umar et al. 2021) or target only residential or commercial green lending. We combine this data with micro-level information from Central Credit Register and debtors' financial information reported to the Ministry of Finance. The extensive time perspective provided by the database (period 2010-2020), allows us to follow developments in the risk profile of green loans over entire business and financial cycles.

The rest of the paper is structured in four parts. In the next section, we present main findings from literature on sustainable finance, with focus on risk differentials between green and non-green loans. The third section describes data and methodology employed in the paper, while the result section presents and explains the main outcomes. The last part of the paper provides the main conclusions, emphasizing possible policy implications from these findings.

## 2. Literature review

A priori, sustainable finance has positive externalities and can improve firms' ability to overcome the impact of climate risks (IMF, 2019). Nevertheless, the lack of reliable historical data limits the evaluations regarding the risk differentials on green loans. The available studies use recent data from Chinese banks and some concentrate on different regions, like the Eurozone or the US. Most of these studies rely on aggregate data, while some employ bank-level information. The novelty that our study brings is the extensive use of micro-level information for non-financial-companies, linking green financing, lending data and firms' financial statements, as well as the coverage of a sufficiently long time-frame.

A large amount of papers delves into China's experience with green lending, which was supported by a wide range of policies since 2007. The majority of them use bank-level data and evaluate the connection between green lending and bank profitability and/or credit risk.

Findings suggest that a higher share of green loans reduces the credit risk of banks on the account of higher risks for borrowers from polluting industries carry. This is mainly due to the lower demand and their sensitivity to transition risks (Cui et al, 2018). In terms of profitability, the results depend on the type of banks' ownership, given the large share of state-owned credit institutions through which the green lending policies are enforced. Findings show that green lending practices have the potential to increase the profitability of non-state-owned banks in China, while also reducing their risks. However, for state-owned banks the impact is negative and explained by the government pressure to issue green loans even at the expense of profitability (Yin et al., 2021). Song et al. (2019) also find a positive impact on profitability stemming from green lending but only for international banks. For Chinese banks the impact is negative and explained by the lower development stage of Chinese green firms relative to foreign ones. Furthermore, Weber (2017) finds a bi-directional (positive) causal relationship between the financial and sustainability (especially environmental) performance of Chinese banks.

Based on data from US companies, other studies find that the ESG activity of financial companies is associated with an increased profitability (expressed in ROA), both in the short and long-term. For non-financial companies, they find that this profitability effect slows down in the long-term, which, according to the authors, can be prevented by including ESG investments in the long-term strategy of the companies (Brogi and Lagasio, 2018). Similarly, Umar et al., 2021 conclude that banks from Eurozone benefit from extending credit to carbon-neutral borrowers, identified as low carbon emitters, in that exposure to carbon-neutral investments reduces their credit risk.

Findings from the literature on property markets suggest that the energy efficiency of a property bought with a mortgage is negatively related to the default risk of the mortgage loan, due to factors like reduced energy costs and cheaper home insurance (Billio et al., 2021). Moreover, the default risk of commercial mortgage backed loans seems to be lower, on average, by 34% if the building is energy-efficient (An and Pivo, 2020).

The literature on green financing strongly supports the positive effects of this type of lending on credit risk and profitability. However, caution is required since these conclusions apply only for well-informed financial institutions. Excessive government pressure to increase green loans might actually reduce bank profitability. Zhou et al. (2020) find that the share of green loans can have negative effects on the credit risk in case of Chinese state-owned major banks. This is explained by the lack of necessary information about green lending opportunities increases the chances of bad investment decisions. Other studies find that firms that are better prepared for the low-carbon transition have lower credit risk, as measured by market-implied distance-to-default and credit rating. These firms disclose their emissions and have set their forward-looking target to cut emissions (Carbone et al., 2021).

In this context, a significant risk that lenders might face is greenwashing. As defined by European Commission, greenwashing is the case when companies are giving a false impression of their impact or benefits for the environment, which results in misleading the market actors and disadvantaging other companies that are making efforts to green their activities[3]. European Commission has taken several initiatives in order to combat false environmental claims. In this respect, it is important that creditors include the risk of greenwashing into the credit-risk assessment. Studies find that in case of bank lending, even though greenwashing is not incorporated in higher interest rate spread (evidence show that they even have lower spreads), banks are trying to prevent this risk by applying more complex pricing structure, using a combination of price and non-price contract terms. Therefore, high importance is given to

[3] https://ec.europa.eu/environment/eussd/smgp/initiative_on_green_claims.htm

monitoring capabilities of creditors in order to prevent greenwashing, without limiting access to finance for green loans (Attig, M. Rahaman, S. Trabelsi, 2021).

Another strand of literature examines the necessity of financial policy measures in the fight against climate change and in supporting green investments. The debate is not settled yet and this is especially due to the lack of sufficient findings on the risk profile of green lending (Dakert et al., 2018), a common accepted definition (Thomä and Hilke, 2018) or sufficient historical information. However, postponing the implementation of fiscal measures leads the attention towards financial measures. The studies evaluating the impact of such measures seem to converge on the idea that macroprudential measures, such as differentiated capital requirements, are useful to enhance green lending and investment, but the effect is not large (Punzi, 2018, Dafermos and Nikolaidi, 2021 and Dunz et al., 2021). Several methodological approaches are used, from environmental DSGE models (Punzi, 2018) to macrofinacial stock flow models (Dafermos & Nikolaidi, 2021; Dunz et al, 2021). Dafermos and Nikolaidi (2021) study the implications of green differentiated capital requirements and fiscal measures via several transmission channels. While applying the different capital measures separately, there is evidence of lower fossil fuels use and increasing energy efficiency. The impact is more beneficial when measures are applied together, or even in tandem with a carbon tax. Additionally, Dunz et al. (2021) account for banks climate sentiments as a way to anticipate their movements prior the implementation of climate measures and observe that a green supporting factor can stimulate green finance, however in order for the impact to be significant a large decrease of the interest rate for green loans is necessary.

Other climate policy measures have consequences on financial stability. For example, Ferentinos et al. (2021) assess the consequences of a policy intervention in the housing market, namely imposing a Minimum Energy Efficiency Standard initiative (MEES), and observe a decrease in the prices of low efficient buildings, however with small effects on financial stability.

# 3. Data and methodology

## 3.1. Data and stylized facts

To analyze the credit risk difference between corporate green and non-green loans, we explore a new dataset consisting of all green loans granted by 13 Romanian banks[4] to non-financial companies, over the period 2010-2020. We use loan-level data from the Central Credit Register (CCR) and companies' financial information from the Ministry of Finance (Annex 1, Figure 1). Our final dataset covers approximatively 1.7 million observations, out of which around 4000are classified as green loans[5]. We consider non-financial companies that have at least one loan from one of the 13 banks in the analyzed interval (2010-2020).

In our analysis, green loans are defined as loans granted for projects /investments with the purpose of mitigating the impact of climate change or for the adaptation to climate change challenges. In total, there are seven categories of activities considered: investment in renewable energy, energy efficiency, transport efficiency, green buildings, waste and water usage reduction, financing for energy-efficient technologies and climate change adaptation. The flag for the green loans is introduced as follows:

$$flag\ green_{i,t} = \begin{cases} 1, & the\ loan\ \in green\ categories \\ 0, & otherwise \end{cases}$$

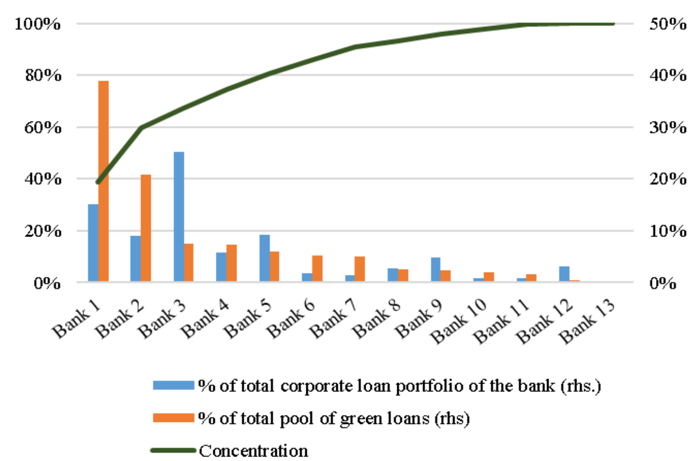
The CCR database provides an extensive amount of information regarding the characteristics of loans, such as currency, maturity, interest rate and payment behavior. Since we want to assess the credit risk of this type of financing, we construct a flag for non-performing exposures, which are defined as loans with more than 90 days past due. Furthermore, we evaluate the financial stance of companies with green loans and assess which factors favor the access to green lending (financials, economic sector, ownership type etc.). The variables used in the paper are detailed in Tables 1.1 and 1.2 (Annex 1).

[4] The banks included in the analysis account for 86 percent of total assets / loans in the banking sector. The data was collected via an exercise conducted by the working group on supporting green finance established by the National Committee of Macroprudential Oversight in 2020, which published its report in June 2021 (http://www.cnsmro.ro/res/ups/Summary-Report-NCMO-green-finance.pdf).

[5] Since firms' financial indicators have an annual frequency and given that probability of default is calculated one-year ahead, we use the same frequency for CCR variables and green loans. As such, the green loans reported by banks that exited their portfolio during the same year could not be identified and are not relevant for our purposes.

However, we identify a limitation to our definition. Since green loans are identified *ex-post*, other criteria besides the scope of the projects financed, such as the do no significant harm criteria (DNSH) or sector specific relevant legislation, are not considered. Therefore, our definition of green loans is not entirely compliant with the EU Taxonomy or other international principles regarding green loans. Therefore, green loans were not designed as such by banks at the time they were granted, being identified as green afterwards. Thus, these products do not have the characteristics of a complex green product, which might include price and non-price contract terms deemed to prevent greenwashing.-.

Chart 1. The concentration of green loans




*Source: NBR, authors' calculations*

The green corporate portfolio is on the rise since 2010, in terms of both outstanding exposures and share in the total corporate portfolio. However, green loans (approx. 1 billion euro at end 2020) account for only 4.2% of the total corporate portfolio and exhibit a high concentration among reporting banks. The first two credit institutions hold approximately 60% of the total green corporate green portfolio (Chart 1).

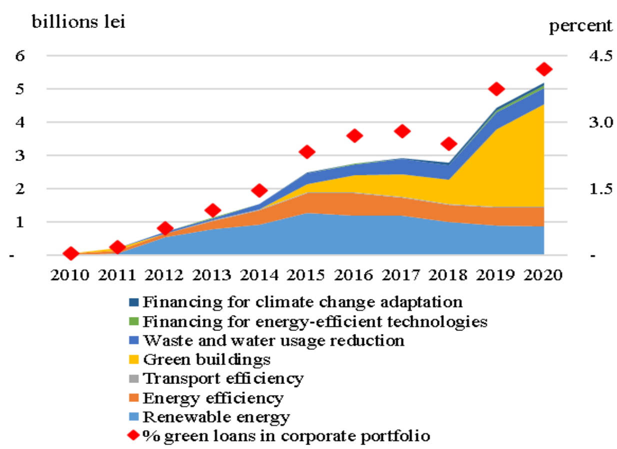
The structure of green lending shows a significant variation in the past decade (Chart 2). At the beginning of the interval, we observe a high interest in energy efficiency projects (85% of all green lending in 2010), but this was soon overtaken by investments in renewable energy. The passing of Law 220/2008 stimulated the growth of renewable energy sources and led to a boom of investments in this segment in a few years. However, several amendments to the regulatory framework led to a deterioration of these projects[6], affecting also the appetite for financing. Following the unforeseen regulatory changes, the non-performing loan ratio (NPL) for renewable

[6] A report by Ernst & Young for Romania Wind Energy Association (RWEA) in 2020, Financial analysis of the Romanian wind power sector shows that the wind power industry saw its assets lose more than one billion lei in value between 2016 and 2018. V. Câmpeanu, S. Pencea, Renewable energy sources in Romania: from a "paradise" of investors to a possible abandon or to another boom? The impact of a new paradigm in Romanian renewable sources policy, 2013

projects increased from almost 0% to around 20% in 3 years. Additionally, using the harmonized definition proposed by European Banking Authority (EBA)[7], we observe that starting 2015 especially the unlikeliness to pay is on an upward trend (Chart 3), due to the uncertainty in the legislative framework. The current stage marks the lead of investments in green buildings (almost 60% of all green bank loans).

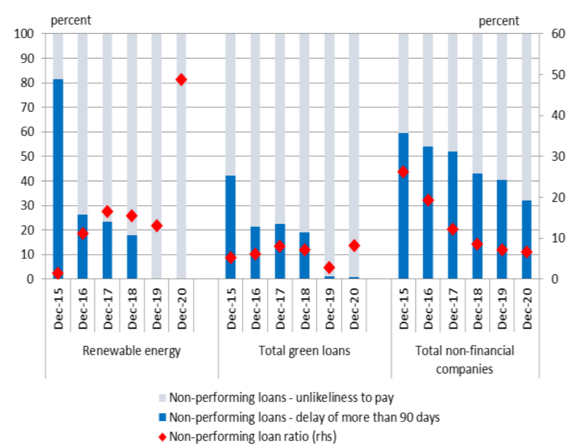
Several characteristics of the current green portfolio indicate that either financially-worth companies applied for a green loan (the demand effect) or banks had a better selection strategy for these debtors (the supply effect). However, this is not necessarily a prerequisite for future green lending. We cannot anticipate the quality of future green products, especially since access to green finance is expected to expand.

Chart 2. Total green bank loans to non-financial companies




Source: NBR, authors' calculations

Chart 3. Non-performing loan ratio (NPL)* of green loans




*according to European Banking Authority (EBA) harmonised definition

*Source: NBR, authors' calculations*

First, companies with green loans have, overall, a better financial position[8], in terms of indebtedness and liquidity, compared to those without this type of financing. Second, the average value of green corporate loans is substantially higher compared to the entire corporate portfolio (6.5 million lei vs. 0.66 million lei, as of 2020). Additionally, foreign-owned firms contract substantially higher green loans (almost 7 times larger), in contrast to domestic-owned entities.

[7] In 2014 the EBA introduced a harmonized definition across European countries of NPLs, which has been the benchmark for monitoring the asset quality of the European banking sector. The data is only available since April 2015.

[8] According to 2020 annual financial statements, in case of companies that were still active.

The fact that foreign-owned firms borrow more and at a larger scale from domestic banks could indicate that they are more environment-conscious and readier to decarbonize their activity. Moreover, green corporate loans have, on average, a maturity of 6 years, indicating the use of proceeds for long-term investments, and not only for short-term expenditures (Annex 2, Chart 3 A). Also, since 2015, interest rates[9] on loans to non-financial firms were in general higher than those on green loans, reflecting either a strategy for increasing the green portfolio or an inherent lower risk associated to the borrowers (Annex 2, Chart 3 B).

The good quality of the green portfolio is reflected in the NPL ratios, which remain below the level for the entire corporate portfolio over the whole period. However,

## 3.2. Methodology

This study proposes a three-step approach in order to assess the risk differentials between the two portfolios (green and non-green) in a robust manner.

First, using a logit specification, we estimate the probability of a firm to take a green loan. This allows us to identify the main characteristics of companies that accessed this type of financing. We strive to determine whether firms with green lending have a better financial standing, in terms of profitability, efficiency or indebtedness, as well as their investment capacity. We use the logit specification in order to account for the possible non-linearities, but also to take into consideration the non-normality and heteroscedasticity of the error term in the true probability model. Additionally, to mitigate the selection bias generated by the limited sample of green loans, compared to other loans, we use a bootstrap estimation. The dependent variable is the dummy variable constructed for green loans (*flag_green*).

The likelihood function (transformed then into a log-likelihood) used in the regression is the following:

$$\mathrm{L}(\beta) = \sum_{t=0}^{T} \sum_{i=0}^{n} \Lambda(P_{it})^{y_{it}} (1 - \Lambda(P_{it}))^{1-y_{it}} \qquad \text{(eq.1)}$$

[9] Average interest rates, regardless of maturity or currency

with $\Lambda$ being the logit function, $y_{it}$ the dependent variable (*flag_green*) and $P_{it}$ the probability function in the logit specification, given as such:

$$Logit(P_{it}(Y_{i,t} = 1 | x_1, x_2 \ .. x_n)) = \alpha_i + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it} \qquad \text{(eq.2)}$$

where: $\mathbf{x'}_{it}$ is the transpose vector of explanatory variables for an observation *i* at period *t*, $\boldsymbol{\beta}$ is the vector of coefficients, and $\varepsilon_{it}$ is the error term. We estimate a pool logit model and, for robustness, we also test the importance of time effects. Additionally, for robustness purposes, each regression was (re)estimated 100 times using a sample of 100 000 observations out of the total of around 1.7 million.

For the explanatory variables we consider firm characteristics, such as financial soundness indicators, arrears and the economic sector (details regarding the variables used are included in Table 1.2 in Annex 1). We start from a benchmark estimation and test additionally several other variables, selecting the final specification according to a range of selection criteria (adjusted R squared, ROC and AUC). In all specifications, variables are considered with one-year lag.

In the second step, we aim to evaluate whether green loans have a lower credit risk compared to non-green loans, more precisely, whether the greenness of a loan *per se* has a causal effect on the default risk. We use a logit model with a similar specification as in equation 2 in order to explain the *default.* This specification is replicated 100 times in order to mitigate the selection bias.

In this case, the dependent variable ($Y_{i,t}$) is a dummy taking the value 1 when the loan reaches more than 90 days past due and 0 otherwise, based on a subset of the standard definition of default[10]. The explanatory variables are selected starting from the default model used in Costeiu & Neagu (2013), to which we add the *flag_green*.

$$Logit(P_{it}(Y_{i,t} = 1 | z_1, z_2 \ .. z_n)) = \Phi_i + Fin\ ind_{i,t}\beta_1 + \ flag\_green_{i,t}\beta_2 + \varepsilon_{it} \qquad \text{eq.3}$$

In the third and final stage, we seek to further test the accuracy of our results from the previous method. We do this by checking if having a green loan truly diminishes the companies' probability of the default and that the outcome is not affected by the overall better financial standing of these firms. Thus, starting from the selected specifications in the previous steps, we

[10] We do not use the EBA definition of default, which includes additionally the unlikeliness to pay criteria, because it would restrict our analyses to the period 2015-2020.

estimate the average treatment effect (ATE) between green and non-green loans, using three types of estimators: a propensity score matching (PSM), an inverse-probability-weighted regression adjustment (IPWRA) and an augmented inverse-probability weighted estimator (AIPW). The average treatment effect overcomes the problem of "causal inference" generated by the fact that we observe only one potential outcome for each observation, treated or not, respectively with or without a green loan. The approach has gained importance especially when analyzing a policy measure implication (Alam et al., 2019, Jorda et al., 2016).

The propensity score matching estimator uses a treatment model to combine a series of covariates, included in the logit model presented at step 1, and calculates the propensity scores or the treatment probability and these are further used as matching variables. The other two estimators, AIPW and IPWRA, categorized as "double-robust" estimators, allow the assessment of both the treatment and outcome models. These estimators use the inverse-probability weights from the treatment model, as following:

- the IPWRA estimator employs the weights for estimating the outcome model, the default model in our case
- the AIPW computes the weighted average means of treatment specific predicted outcome models.

All three methods account for the potential missing information in our sample, given the lower number of observations for green lending relative to the size of the overall sample. Moreover, given the double robustness feature of the AIPW and IPWRA, the estimator stays consistent even if one of the models, treatment or outcome, is not specifies properly (Glynn and Quinn, 2009; Woolridge, 2007). The PSM estimator requires very intensive computing and is estimated on a random 10 percent sample of our database, while for the other two estimators we use the entire database.

# 4. Results

## 4.1. Results for the green loan determinants model

In the first step, we analyze the profile of firms with green loans. Given that for the timeframe analyzed, green products were not defined specifically in banks' credit offer, we focus on the demand factors and less on the supply channel. We apply a multivariate logit regression model with financial indicators as explanatory variables and we use a bootstrapping technique to reduce the bias of the small share of green loans.

The results of different specifications indicate that these firms tend to be in a superior financial standing, have higher profit margins and invest more (Table 1). The positive coefficients for the ratio of earnings before interest, taxes, depreciation and amortization (EBITDA) to total sales and, as well the share of fixed assets to total assets support these findings. Our results are in line with findings from Brogi and Lagasio (2018), who show evidence of the positive impact that ESG activities have on US firms' profitability. This can also suggest that companies that invest more are usually more concerned with the impact of their activities on climate and are willing to put up a stake of their profits to better adapt to the climate change impact on their activity or to surpass consumer expectations. In addition, these firms are characterized by a lower degree of indebtedness and are less prone to generate payment arrears in relation to non-bank partners. Moreover, as a robustness check, the coefficients' average value from the bootstrapping exercise was relatively close to our initial estimates (Table 1, Annex 2). The model results support the data findings presented in Section 2.

We also account for the economic sectors by means of a dummy variable introduced in the third specification (Table 1) and find that companies operating in utilities, agriculture and manufacturing are more probable to access a green loan. This is in line with the results from NBR (2019), which shows that firms in these sectors are more likely to be affected by physical and transition risks, the former being particularly relevant for agriculture. One venue through which firms could try to mitigate the climate risk impact would be via bank funding, which would allow them to readjust their operations to a more environmentally friendly approach and to benefit from the opportunities brought forward by the green transition. In case of mining, the dummy's negative coefficient signals that credit institutions might no longer be inclined to finance this sector given the current priorities, at European and national level.

With further robustness verification in mind, we use also the full sample, including the total exposures in the banking sector and observe similar results (Table 2, Annex 2). Second, we insert time effects in the selected specification, to control for the instances when the economic situation in a particular year could influence our outcome (Table 1, column 4). Additionally, we also restrict the timeframe at the period 2015-2020, as green lending gains more traction among banks (Table 1, column 5). Results remain in the same range and signs are unchanged.

**Table 1. Green loan determinants model**

| | Full sample (2010-2020) | | | | 2015-2020 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Fixed assets/ Total assets $_{t-1}$ | 0.009*** (0.00) | 0.009*** (0.00) | 0.005*** (0.00) | 0.010*** (0.00) | 0.014*** (0.00) |
| EBITDA/CA $_{t-1}$ | 0.008*** (0.00) | 0.008*** (0.00) | 0.007*** (0.00) | 0.004*** (0.00) | 0.006 *** (0.00) |
| Debt/Total assets $_{t-1}$ | -0.003*** (0.00) | -0.003*** (0.00) | -0.002*** (0.00) | -0.003*** (0.00) | -0.003*** (0.00) |
| Non-bank arrears/ Total assets $_{t-1}$ | 0.019*** (0.00) | | | | |
| Sales/Total assets $_{t-1}$ | | -0.000* (0.09) | | -0.001*** (0.00) | -0.002*** (0.00) |
| Dummy agriculture | | | 0.006*** (0.00) | | |
| Dummy mining | | | -0.001 (0.45) | | |
| Dummy manufacturing | | | 0.005*** (0.00) | | |
| Dummy utilities | | | 0.018*** (0.00) | | |
| Dummy construction | | | -0.002 (0.23) | | |
| Dummy trade | | | -0.001 (0.40) | | |
| Dummy services | | | -0.003*** (0.01) | | |
| Dummy real estate | | | 0.002 (0.20) | | |
| | | | | | |
| Time effects | No | No | No | Yes | Yes |
| Observations | 563,971 | 563,971 | 563,971 | 563,971 | 338,056 |
| Log likelihood | -14673.55 | -14,35.50 | -11744.85 | -14296.92 | -12448.157 |
| Pseudo R2 | 5.9% | 5.5% | 24.6% | 8.36% | 5.03% |

| | | | | | |
|---|---|---|---|---|---|
| ROC | 74.0% | 73.4% | 86.6% | 78.1% | 71.54% |
| Accuracy ratio | 47.9% | 46.8% | 73.3% | 46.1% | 43.08% |

Note: All estimations are carried using the data for the 13 reporting banks, for the period 2010-2020 if is not specified otherwise. A bootstrapping technique, specifically using 100 repetitions and 100 000 observations samples.
The values represent the marginal effects and, in parentheses the p-values: * p<0.10, ** p<0.05, *** p<0.01

### 4.2. Results for the probability of default model

The second step consists of verifying whether firms that accessed green funding are less risky from a credit perspective. The credit risk model configuration starts from Costeiu and Neagu (2013), and is adapted to include the flag of green loan at company level.

The results indicate that companies with green loans have a lower PD, the coefficient for the *flag_green* being negative across all specifications, confirming our initial hypothesis (Table 2). This conclusion is also supported by Cui et al. (2018), who find evidence that an increasing share of green lending has a positive effect on credit risk. The observed risk differential holds irrespective of firm type, the technological intensity of the manufacturing industry or the knowledge intensity of the services.[11] However, the results are mixed when discerning between green lending granted to companies with a lower technological intensity versus firms operating in high-tech, as well as between green financing to less-knowledge intensive services and those firms that rely heavily on knowledge (Table 2, Annex 1).

Our results also show that firms with a better capacity to generate profits have a greater ability to service their bank debt and, thus, a lower probability to default on a loan. Another factor that reduces the prospects of default is having an improved efficiency in the use of available assets: a superior ability to generate more sales while employing the same or a lower amount of assets diminishes the PD. Moreover, a higher rate of investment proves to have a curtailing effect on firms' default risk, indicating that companies that always look either to develop new cash-flow generating activities or to improve their effectiveness in terms of costs have a lower chance to end up in default. The same is true for firms that maintain an adequate level of indebtedness, as our results indicate that companies that take on too much debt have a larger probability of not being able to service their debt.

[11] Eurostat aggregations of manufacturing and services based on NACE Rev. 2, https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf

**Table 2. Probability of default – logit model estimation**

| | Full sample (2010-2020) | | | | | 2015-2020 |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Fixed assets/ Total assets | -0.211*** (0.00) | -0.201*** (0.00) | -0.138*** (0.00) | 0.070*** (0.00) | -0.079*** (0.00) | -0.140*** (0.00) |
| EBITDA/CA | -0.435*** (0.00) | -0.349*** (0.00) | -0.201*** (0.00) | -0.274*** (0.00) | -0.130*** (0.00) | -0.161*** (0.00) |
| Debt/Total assets | -0.003* (0.05) | -0.006*** (0.01) | 0.039*** (0.00) | 0.053*** (0.00) | 0.028*** (0.00) | 0.036*** (0.00) |
| Flag green | -0.129** (0.00) | -0.144*** (0.00) | -0.136*** (0.00) | -0.134*** (0.00) | -0.064*** (0.00) | -0.098*** (0.01) |
| Arrears/Total assets | 0.286*** (0.00) | | | | | |
| ROA | | -0.203*** (0.00) | | | | |
| Sales/Total assets | | | -0.191*** (0.00) | | -0.098*** (0.00) | -0.178*** (0.00) |
| Dummy agriculture | | | | -0.300*** (0.00) | | |
| Dummy mining | | | | -0.232*** (0.00) | | |
| Dummy manufacturing | | | | -0.284*** (0.00) | | |
| Dummy utilities | | | | -0.272*** (0.00) | | |
| Dummy construction | | | | -0.252*** (0.00) | | |
| Dummy trade | | | | -0.304*** (0.00) | | |
| Dummy services | | | | -335*** (0.00) | | |
| Dummy real estate | | | | -0.310*** (0.00) | | |
| | | | | | | |
| Time effects | No | No | No | No | Yes | Yes |
| No. obs | 1,406,523 | 1,406,523 | 1,406,523 | 1,406,523 | 1,406,523 | 783,692 |
| Log. Likelihood | - 465554.42 | -474691.05 | - 346779.10 | -346779.10 | - 328557.03 | -126062.3 |
| Pseudo R2 | 15.64% | 13.99% | 37.6% | 29.73% | 40.47% | 33.35% |
| ROC | 80.14% | 78.63% | 90.11% | 85.48% | 91.32% | 89.71% |
| Accuracy ratio | 60.28% | 57.26% | 80.22% | 70.96% | 82.64% | 79.42% |

Note: All estimations are carried using the data for the 13 reporting banks using a bootstrapping technique. More specifically, we impose 100 repetitions and 100 000 observations samples.
The values represent the marginal effects and, in parentheses the p-values: * p<0.10, ** p<0.05, *** p<0.01

The results hold if we include time effects or restrict the timeframe to the interval 2015-2020. For example, in the final specification (Table 2, column 3), accounting for time effects or restricting the sample exhibits the same importance for the financial variables, however reduces slightly the coefficient for firms with green loans.

We also evaluate several specifications of the multivariate logit model, by running a full-sample estimation that includes all banks and companies with loans, not only the 13 banks that participated in the green lending data collection exercise (Table 3, Annex 2). The purpose was to investigate whether the conclusions still hold in this scenario, as well. The results indicate relatively similar value of coefficients and sign, which was to be expected given that the credit institutions participating in the questionnaire represent a market share of over 80 percent.

## 4.3. Robustness assessment of risk differentials

In the third step, we apply several specifications of an average treatment effect model (ATE). We do this in order to assess the robustness of the previous results regarding the risk differential between green and non-green loans.

Given the lower number of companies with green loans relative to the overall database and, implicitly, the reduced number of defaults, we use several average treatment effects (ATE) methods, to cope with endogeneity problems and validate the findings that having a green loan has an attenuating effect on the probability of default. To this end, we used the propensity score matching, the inverse-probability-weighted regression adjustment and the augmented inverse-probability weighting. All three approaches signal that companies with green loans are less likely to default on their bank loans, with an average decreasing effect on the PD of 10 percent (Table 3).

**Table 3. Average treatment effects results**

| | Average treatment effect (ATE) | | |
|---|---|---|---|
| Method | Propensity Score Matching | Inverse-probability-weighted regression adjustment | Augmented inverse-probability weighting |
| Flag green loan (1 vs. 0) | -0.0879***<br>(0.00666) | -0.126***<br>(0.0124) | -0.116***<br>(0.0103) |

Note: p-values in parentheses
* p<0.10, ** p<0.05, *** p<0.01

The results are in line with the existing literature and point to a better repayment capacity of these firms compared to those without green loans. However, we identify several limitations. First, we construct our analysis on a portfolio of loans categorized as green on the account of a working definition and not based on the internationally approved standards, due to the limited capacity to identify ex-post such loans. Second, the lack of well-established green products at bank level allow us to evaluate only demand factors for the probability of getting such a loan. Third, the limited amount of data does not allow a proper investigation for each category of green projects. This will be subject to further investigations, once the new data will be gathered.

## 5. Conclusions

In our paper, we investigate if green loans granted by banks are less risky compared with the rest of loans. We use a novel micro database, covering all green exposures delivered by the largest Romanian banks, during 2010-2020 period. We also analyze the characteristics of companies that borrow from banks to finance their green projects, using individual data from Central Credit Register and fiscal authorities' database.

The main conclusion is that green loans bear less credit risk compared with non-green loans. We compute the probability of default (PD) for companies that took loans in order to finance green projects with the PDs for companies having non-green loans and we discover that credit risk is 10 percent lower in the first category. The conclusion remains viable also after we control for endogeneity, using an average treatment effects model. Moreover, the non-performing ratio for green loans remains inferior compared with the rest of banks corporate' portfolio. From a policy perspective, such outcome would plea for lower capital requirements for green exposures compared with non-green loans. The question is whether the allowance for such capital reduction should be run through lower risk weights applied in computing solvency ratios (i.e. Pillar 1 measures) or through Pillar 2 actions (i.e. the decision of the microprudential supervisory authority). Our findings would underpin the second option, for at least three reasons.

First, one additional result of our paper is that sounder companies (displaying lower indebtedness and upper profit margin and liquidity) are more prone to take green loans. From the banking perspective, lending standards for green loans stood tighter during 2010-2020. However, a future unsustainable surge in green finance might ease lending standards and increase greenwashing, with negative consequences for credit risk. Authorities and investors pressure to increase green finance would bring on banks' radar companies with less sound financial profile. Microprudential authorities are in a better position to evaluate such possible deterioration in green lending standards and may swifter recalibrate capital requirements through Pillar 2 compared with regulatory authorities' ability to readjust risk weights for solvency purposes.

Second, amendments in government plans regarding climate change strategies might deteriorate companies' ability to repay green loans. For example, we notice an increase in the unlikeliness to pay for firms acting in renewable energy industry after the Romanian authorities modified the legal framework within short notice (the NPL ratio increase from almost 0% to around 20% in 3 years). Future amendments are very probable, having in mind that climate change agenda implies policies spanning on decades. From a financial stability perspective, microprudential supervision authorities are more equipped to react through amendments to Pillar 2 requirements for green exposures compared with regulatory authorities, if material changes in legal framework for green projects would manifest.

Third, innovation in green area most likely will continue to expand in all economic sectors, with consequences on credit risk. Although not limited to this groups, we reach mixed results when computing probability of default for green loans granted to firms in higher value added sectors (medium and high-tech industries and knowledge intensive services) compared with PDs for green loans granted to firms acting in less innovative sectors (low and medium low tech industries and less knowledge intensive services). This mixed outcome call for flexibility in dealing with potential measures for reducing capital requirements regarding green exposures, where Pillar 2 decisions are best suited to capture such need for flexibility.

# Bibliography

Alam, Z., Alter, A., Eiseman, J., Gelos, G., Kang, H., Narita, M., Nier, E. & Wang, N. “Digging Deeper—Evidence on the Effects of Macroprudential Policies from a New Database”, IMF WP, No.66, 2019.

An, X. and Pivo, G. "Green Buildings in Commercial Mortgage-Backed Securities: The Effects of LEED and Energy Star Certification on Default Risk and Loan Terms." *Real Estate Economics* 48, No. 1, 7-42, 2020.

Attig N., Rahaman M., Trabelsi S., "Greenwashing and Bank Loan Contracting: Does Environmental Disclosure Quality Matter to Creditors?", 2021, Available at SSRN: https://ssrn.com/abstract=3880113 or http://dx.doi.org/10.2139/ssrn.3880113

Billio, M., Costola, M., Pelizzon, L. and Riedel, M. "Buildings' Energy Efficiency and the Probability of Mortgage Default: The Dutch Case." *Journal of Real Estate Finance & Economics*, 2021, https://doi.org/10.1007/s11146-021-09838-0.

Brogi, M. and Lagasio, V. "Environmental, social, and governance and company profitability: Are financial intermediaries different?" *Corporate Social Responsibility and Environmental Management*, 2018: 576-587.

National Committee of Macroprudential Oversight, "Analiza Grupului de lucru CNSM pentru sprijinirea finanțării verzi." 2021.

Carbone, S., Giuzio, Kapadia, S., Krämer, J. S., Nyholm, K. & Vozian, K., "The low-carbon transition, climate commitments and firm credit risk", ECB WP, No. 2631 (2021)

Costeiu, A. & Neagu, F. "Bridging the banking sector with the real economy. A financial stability perspective", ECB WP , No. 1592, (2013)

Cui, Y., Geobey, S., Weber, O. and Lin, H. "The Impact of Green Lending on Credit Risk in China." *Sustainability* 10, No. 6, 2018.

Dafermos, Y. and Nikolaidi, M. "How can green differentiated capital requirements affect climate risks? A dynamic macrofinancial analysis", Journal of Financial Stability No. 54 100871, 2021.

Dankert, J., van Doorn, L., Reinders, H. J. and Sleijpen, O. "A Green Supporting Factor — The Right Policy?", SUERF Policy Note No. 43, 2018.

Dunz, N., Naqvi, A. and Monasterolo, I. "Climate sentiments, transition risk, and financial stability in a stock-flow consistent model", Journal of Financial Stability No.54, 100872, 2021.

European Banking Authority, "Mapping climate risk: Main findings from the EU-wide pilot Exercise", 2021.

European Commission, Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the regions - Strategy for Financing the Transition to a Sustainable Economy, July 2021.

Glynn, A. N. and Quinn, K.M., " An Introduction to the Augmented Inverse Propensity Weighted Estimator", Oxford University Press, 2009.

International Monetary Fund, Global Financial Stabilit Report, Chapter 6 - Sustainable finance, October 2019.

Park, H. și Kim J.D., "Transition towards green banking: role of financial regulators and financial institutions", Asian Journal of Sustainability and Social Responsibility, 2020

Song, X., Deng, X. and Wu, R. "Comparing the Influence of Green Credit on Commercial Bank Profitability in China and Abroad: Empirical Test Based on a Dynamic Panel System Using GMM." *International Journal of Financial Studies*,7(4), 64, 2019.

Thomä, J. and Hilke, A. "The Green Supporting factor. Quantifying the impact on European banks and green finance", 2 Degrees Investing Initiative WP No.1, 2018.

Umar, M., Ji, X., Mirza, N. and Naqvi, B. "Carbon neutrality, bank lending, and credit risk: Evidence from the Eurozone." *Journal of Environmental Management*, No. 296, 2021.

Weber, O.. "Corporate Sustainability and Financial Performance of Chinese Banks." *Sustainability Accounting, Management and Policy Journal* 8(3), 358-385, 2017.

Wooldridge, J.M., Inverse probability weighted estimation for general missing data problems. Journal of Econometrics 141, 128, 2007.

Yin, W., Zhu, Z., Kirkulak-Uludag, B. and Zhu, Y. "The determinants of green credit and its impact on the performance of Chinese banks." *Journal of Cleaner Production*, Volume 286 (2021).

Zhou, X., Caldecott, B., Hoepner, A. and Wang, Y. "Bank Green Lending and Credit Risk. An Empirical Analysis of China's Green Credit Policy", University of Oxford WP, No. 8, 2020.

**Figure 1. Main data sources for the information used in the models**

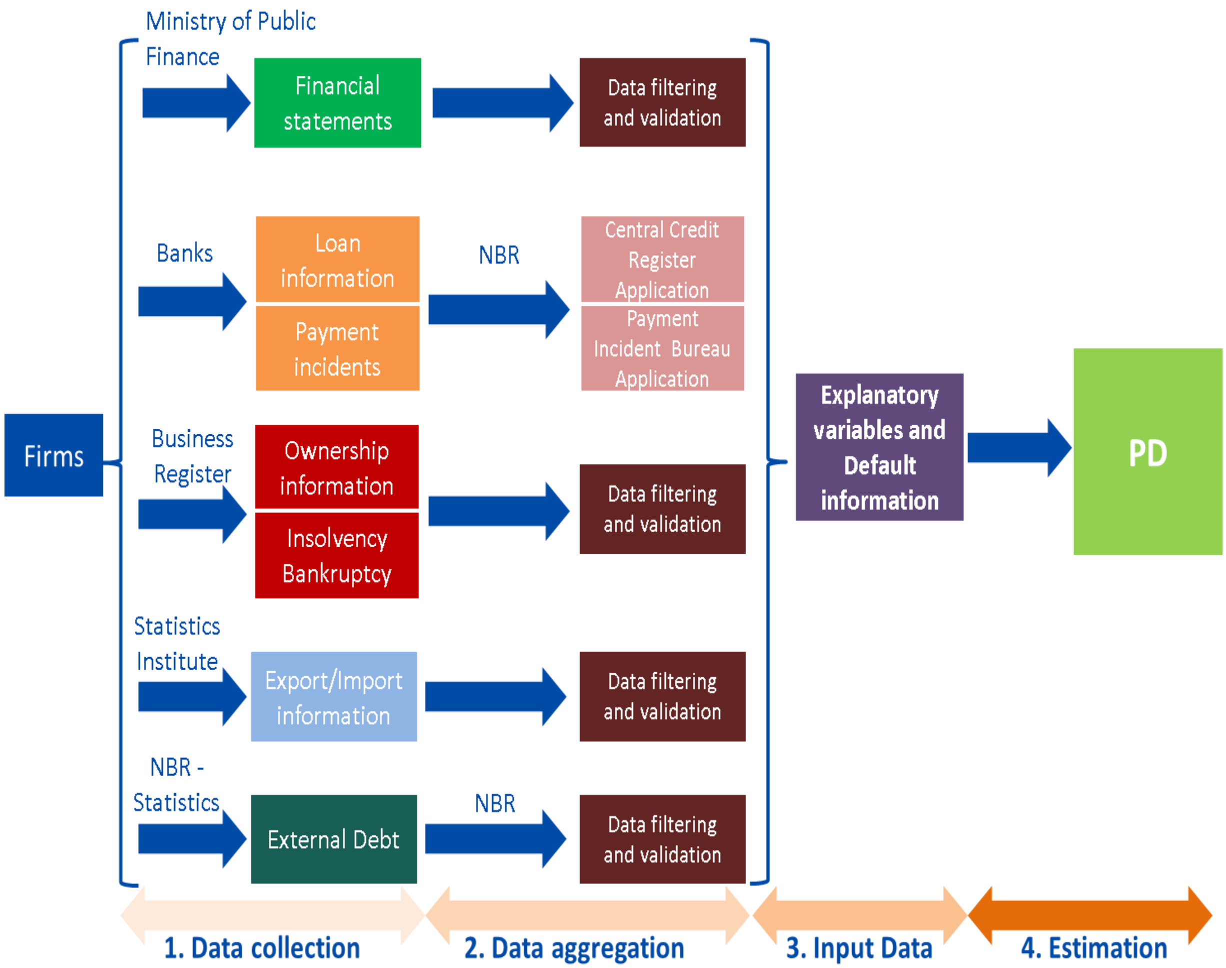


**Table 1.1. Descriptive statistics**

**thousands euro**

| | No. obs | Average exposure | Std. dev | Min | Max |
|---|---|---|---|---|---|
| All green loans | 4288 | 1,191.20 | 4,244.25 | - | 68,375.17 |
| All non-green loans | 1402235 | 148.14 | 1,133.32 | - | 166,079.50 |
| Green loans 2015 | 498 | 1,029.57 | 3,659.56 | 0.04 | 53,723.35 |
| Green loans 2016 | 480 | 1,208.03 | 3,851.62 | 0.16 | 41,512.20 |
| Green loans 2017 | 508 | 1,183.34 | 3,804.66 | 0.24 | 37,738.36 |
| Green loans 2018 | 613 | 973.30 | 3,004.62 | - | 33,964.52 |
| Green loans 2019 | 684 | 1,358.85 | 4,986.55 | - | 65,492.50 |
| Green loans 2020 | 811 | 1,318.50 | 4,712.70 | - | 65,243.12 |

Note: Data on green loans prior to 2015 is particularly scarce, situated on average at around 130 loans/year.

*Source: Central Credit Register, National Bank of Romania, authors' calculations*

**Table 1.2. Non-performing loan ratio by types of loans**

| Default | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Non green loans | 19.53% | 21.95% | 23.89% | 26.38% | 17.14% | 13.47% | 7.67% | 5.78% | 4.92% | 4.46% | 4.32% |
| Green loans | 18.52% | 10.53% | 4.46% | 6.25% | 1.86% | 2.81% | 1.46% | 1.57% | 2.12% | 0.88% | 0.74% |

Note: non-performing exposures classified using the 90 days past due criterion

*Source: Central Credit Register, National Bank of Romania, authors' calculations*

More than 86% of total loans (1,535,509) are performing loans, while the rest (239,239 observation) are loans that defaulted during the analyzed period. The default rates of green category remains below the non-green category over the entire period. In total only 94 observed defaults among green loans (2%) are observed at December 2020, compared to 239,197 defaults for the non-green loans portfolio (13%)

Table 2. Probability of default (PD) by type of loan and firm category*

| Probability of default | Low and medium - low tech | | Medium-high and high tech | | Less knowledge-intensive services | | Knowledge-intensive services | | Rest of the companies | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Green loans | Non-green loans | Green loans | Non-green loans | Green loans | Non-green loans | Green loans | Non-green loans | Green loans | Non-green loans |
| Dec-15 | 1.71% | 4.08% | 1.52% | 3.31% | 2.37% | 3.15% | 3.15% | 4.40% | 3.37% | 4.58% |
| Dec-16 | 2.59% | 3.94% | 2.56% | 3.22% | 2.31% | 4.13% | 4.13% | 4.84% | 3.57% | 4.16% |
| Dec-17 | 1.96% | 3.25% | 2.45% | 2.62% | 1.68% | 3.35% | 3.35% | 3.74% | 2.88% | 3.61% |
| Dec-18 | 2.27% | 4.09% | 2.19% | 3.35% | 2.28% | 2.72% | 2.72% | 4.32% | 3.03% | 4.87% |
| Dec-19 | 2.35% | 3.63% | 1.93% | 3.51% | 2.43% | 2.95% | 2.95% | 3.62% | 2.73% | 4.50% |
| Dec-20 | 2.94% | 4.59% | 2.54% | 4.46% | 3.18% | 3.73% | 3.73% | 4.60% | 3.54% | 5.63% |

*The firm category is based on incorporated technology and knowledge criteria.

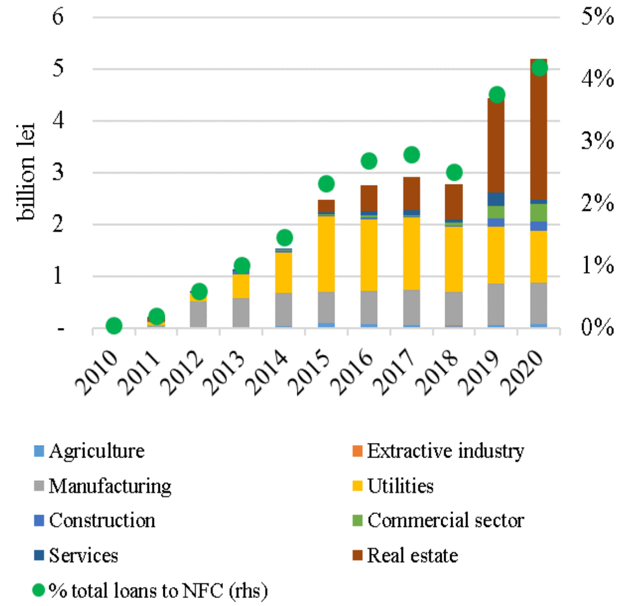
*Source: Central Credit Register, Minister of Finance, National Bank of Romania, authors' calculations*

Table 3. Descriptive statistics of explanatory variables

| | Green loans | | | | | Non-green loans | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | No. obs | Average | Std.dev | Min. | Max. | No. obs | Average | Std.dev | Min. | Max. |
| Fixed assets / Total assets | 4288 | 0.54 | 0.24 | 0.00 | 0.84 | 1402235 | 0.38 | 0.28 | 0.00 | 0.84 |
| Non-bank arrears/Total assets | 4288 | 0.01 | 0.04 | 0.00 | 0.69 | 1402235 | 0.04 | 0.13 | 0.00 | 0.84 |
| Sales/Total assets | 4288 | 0.89 | 0.89 | 0.00 | 4.19 | 1402235 | 1.18 | 1.06 | 0.00 | 4.19 |
| Liquid asset /Total assets | 4288 | 0.07 | 0.11 | 0.00 | 0.96 | 1402235 | 0.08 | 0.14 | 0.00 | 0.99 |
| Dummy payment incidents | 4288 | 0.02 | 0.12 | 0.00 | 1.00 | 1402235 | 0.06 | 0.24 | 0.00 | 1.00 |
| Debt /Assets | 4288 | 0.65 | 0.37 | 0.00 | 7.02 | 1402235 | 0.78 | 0.75 | 0.00 | 7.27 |
| EBITDA /Sales | 4288 | 0.22 | 0.23 | -0.46 | 0.74 | 1402235 | 0.10 | 0.19 | -0.46 | 0.74 |
| Δ Sales | 4288 | 1.01 | 0.44 | 0.00 | 2.04 | 1402235 | 0.92 | 0.51 | 0.00 | 2.04 |
| Δ Debt | 4288 | 1.12 | 0.47 | 0.00 | 2.45 | 1402235 | 1.04 | 0.53 | 0.00 | 2.45 |
| Invest rate | 4288 | 0.10 | 0.18 | -3.63 | 1.02 | 1402235 | -0.52 | 435.13 | -495465 | 22.16 |
| General Liquidity | 4288 | 1.56 | 2.00 | 0.00 | 27.65 | 1402235 | 1.56 | 2.39 | 0.00 | 27.65 |
| Return on assets (ROA) | 4288 | 0.08 | 0.13 | -0.82 | 0.80 | 1402235 | 0.05 | 0.18 | -0.82 | 0.80 |
| Return on equity (ROE) | 4288 | 0.20 | 0.35 | -0.87 | 1.07 | 1402235 | 0.19 | 0.43 | -1.00 | 1.07 |
| Term of debt recovery | 4288 | 99.07 | 83.84 | 0.00 | 303.48 | 1402235 | 81.21 | 85.95 | 0.00 | 303.48 |

Source: *Central Credit Register*, *Minister of Finance*, *National Bank of Romania*, *authors' calculations*

**Chart 1. The structure of green lending by economic sectors**




*Source: NBR,, authors' calculations*

**Chart 2. Value of green loans and no. of companies, by ownership type**

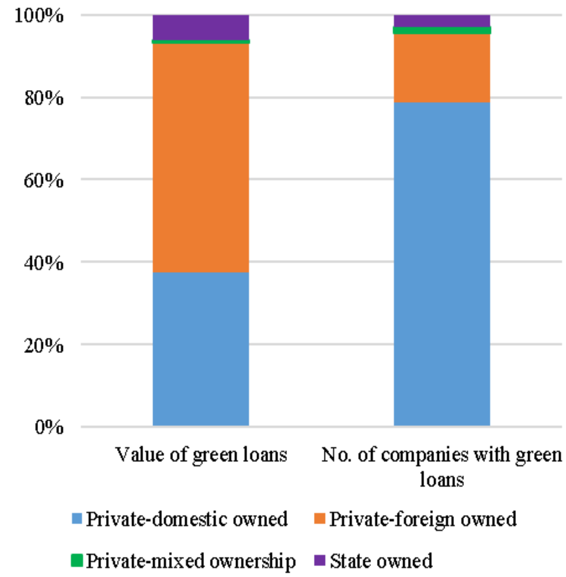
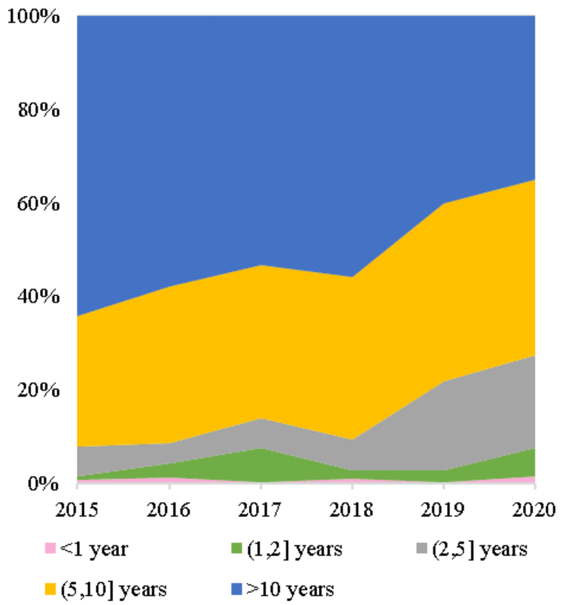
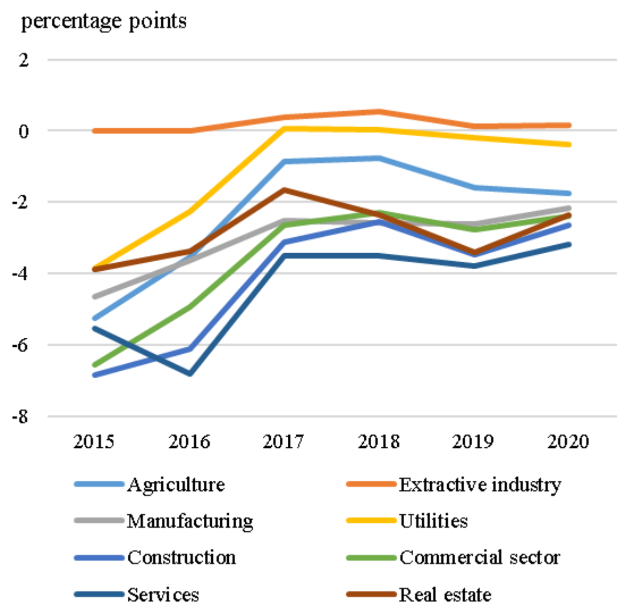



**Chart 3. Lending conditions for green and non-green loans**

A. Green portfolio structure by maturityB. Borrowing costs (interest rate spread*), by sector




**interest rate for green loans – general interest rate*

*Source: NBR, authors' calculations*

## Annex 2 - Additional results

**Table 1. Probability of default model – bootstrap logit estimation**

| | Coefficient | Bias | Bootstrap Std. Err. | [95% Conf. Interval] | | |
|---|---|---|---|---|---|---|
| Fixed assets/Total assets | -1.868*** | 0.004 | 0.046 | -1.958 | -1.778 | (N) |
| | (0.0461) | | | -1.938 | -1.755 | (P) |
| | | | | -1.935 | -1.755 | (BC) |
| EBITDA/CA | -2.669*** | -0.006 | 0.064 | -2.794 | -2.544 | (N) |
| | (0.0639) | | | -2.843 | -2.574 | (P) |
| | | | | -2.843 | -2.574 | (BC) |
| Debt/Total assets | 0.465*** | 0.000 | 0.019 | 0.428 | 0.503 | (N) |
| | (0.0191) | | | 0.423 | 0.496 | (P) |
| | | | | 0.423 | 0.496 | (BC) |
| Flag green loan | -1.701*** | -0.135 | 0.569 | -2.581 | -2.415 | (N) |
| | (0.569) | | | -2.575 | -2.413 | (P) |
| | | | | -2.572 | -2.408 | (BC) |
| Sales/Total assets | -2.498*** | -0.006 | 0.042 | -2.816 | -0.585 | (N) |
| | (0.0423) | | | -2.985 | -0.815 | (P) |
| | | | | -2.796 | -0.812 | (BC) |
| Constant | 0.0546*** | 0.000 | 0.017 | 0.021 | 0.088 | (N) |
| | (0.0173) | | | 0.023 | 0.091 | (P) |
| | | | | 0.023 | 0.091 | (BC) |

(N) normal confidence interval

(P) percentile confidence interval

(BC) bias-corrected confidence interval

Note: p-values in parentheses
* p<0.10, ** p<0.05, *** p<0.01

**Table 2. Green loan determinants - logit model estimation (full sample)**

| | Full sample* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Fixed assets/Total assets$_{t-1}$ | 2.26*** (0.00) | 2.20*** (0.00) | 1.32*** (0.00) |
| EBITDA/CA$_{t-1}$ | 1.84*** (0.00) | 1.89*** (0.00) | 1.74*** (0.00) |
| Debt/Total assets$_{t-1}$ | -0.61*** (0.00) | -0.71*** (0.00) | -0.47*** (0.00) |
| Non-bank arrears/Total assets$_{t-1}$ | -4.21*** (0.00) | | |
| Sales/Total assets$_{t-1}$ | | -0.11* (0.09) | |
| Dummy agriculture | | | 1.56*** (0.00) |
| Dummy mining | | | -0.26 (0.63) |
| Dummy manufacturing | | | 1.29*** (0.00) |
| Dummy utilities | | | 4.50*** (0.00) |
| Dummy construction | | | -0.48 (0.37) |
| Dummy trade | | | -0.26 (0.51) |
| Dummy services | | | -0.90* (0.07) |
| Dummy real estate | | | 0.42 (0.37) |
| Constant | -6.53*** (0.00) | -6.41*** (0.00) | -7.04*** (0.00) |
| Observations | 700,749 | 700,749 | 700,749 |
| Log likelihood | -15,437 | -15,495 | -12,335 |
| Pseudo R2 | 5.7% | 5.4% | 24.7% |
| ROC | 74.0% | 73.5% | 86.7% |
| Accuracy ratio | 47.9% | 46.9% | 73.3% |

* all the corporate exposures in the Romanian banking system, including those for banks that didn't report the green loans. For non-reporting banks all exposures are considered non-green.

Note: The values represent the coefficients of the logit model and the p-values are included in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$

**Table 3. Probability of default – logit model estimation (full sample)**

| | Full sample* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Fixed assets/Total assets | -2.31*** (0.00) | -2.16*** (0.00) | -1.87*** (0.00) | -0.35*** (0.0144) |
| EBITDA/CA | -4.45*** (0.00) | -3.53*** (0.00) | -2.67*** (0.00) | -2.24*** (0.0172) |
| Debt/Total assets | -0.06*** '(0.00) | -0.07*** (0.00) | 0.4654*** (0.00) | 0.79*** (0.00663) |
| Flag green loan | -1.25*** (0.00) | -1.36*** (0.00) | -1.70*** (0.00) | -1.71*** (0.109) |
| Arrears/Total assets | 2.85*** (0.00) | | | |
| Return on assets (ROA) | | -1.95*** (0.00) | | |
| Sales/Total assets | | | -2.49*** (0.00) | -1.95*** (0.01) |
| Dummy agriculture | | | | -2.34** (0.02) |
| Dummy mining | | | | -1.59** (0.04) |
| Dummy manufacturing | | | | -1.66*** (0.0149) |
| Dummy utilities | | | | -1.66*** (0.03) |
| Dummy construction | | | | -1.50*** (0.01) |
| Dummy trade | | | | -1.68*** (0.01) |
| Dummy services | | | | -2.23*** (0.01) |
| Dummy real estate | | | | -2.99** (0.02) |
| Constant | -1.04*** (0.00) | -0.92*** (0.00) | 0.05*** (0.00) | 0.43*** (0.00474) |
| Observations | 1,774,800 | 1,774,800 | 1,774,800 | 1,774,800 |
| Log likelihood | -586,912 | -597,979 | -439,536 | -419,394 |
| Pseudo R2 | 16.4% | 14.8% | 37.4% | 40.3% |
| ROC | 80.6% | 79.0% | 90.2% | 91.1% |
| Accuracy ratio | 61.2% | 58.1% | 80.3% | 82.1% |

* all the corporate exposures in the Romanian banking system, including for banks that didn't report the green loans. For non-reporting banks all exposures are considered non-green.

Note: The table presents the coefficients of the logit model and the p-values are included in parentheses: * p<0.10, ** p<0.05, *** p<0.01