



EBA Policy Research Workshop “*Technological Innovation, Climate Finance and Banking Regulation*”

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# Are green loans less risky? Micro-evidence from a European Emerging Economy

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Note: The opinions expressed in this presentation are those of the authors and do not necessarily reflect the views of the National Bank of Romania

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# Agenda

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1. Context and motivation
2. Literature review
3. Data and methodology
4. Results
5. Conclusions

# Context

## - Increased focus on green finance at global and national level-

- Green finance is needed for the green transition, has positive externalities (IMF 2019) and **could** contribute to lowering firms' current expenses
- Steps at national level:
  - **December 2019:** assessing banks exposures to transition risk and the impact of setting a carbon tax
  - **September 2020:** NBR became part of NGFS
  - **Fall 2020:** NBR carried out a questionnaire regarding climate risk
  - **October 2020:** The National Committee for Macroprudential Oversight (NCMO) set up a WG to support green finance coordinated by NBR
  - **July 2021:** NCMO issued the Recommendation No R/ 6 2021 on supporting green finance

# Motivation & research questions

- Carbon-intensive companies account for a significant share of the Romanian economy (around half), so **new financing means might be needed for the decarbonization of their activity** => *Q 1: Who accessed green loans so far?*
- Green finance is **still** limited, but is expected to play a more important role in the future => *Q2: Do green loans behave differently compared to other bank loans?*
- **Prudential authorities (micro or macro)** should/might ask whether setting differentiated capital req. for green exposures is justified from a risk perspective?

# Literature review

- ❑ Impact of China's Green Lending Policy enforced by the government starting with 2007 on banks' risk and profitability: **Cui et al. (2018), Zhou et al. (2020), Yin et al. (2021)** make the case of accounting for the size and ownership of banks when assessing drivers of green credit ratios (GCR) and impact on profitability
- ❑ **Umar et al. (2021)** show that **banks from Eurozone** benefit from extending credit to carbon neutral borrowers, witnessing a reduction of their credit risk
- ❑ Effects for NFCs: findings suggest that the profitability effect slows down in the long term (**Brogi and Lagasio, 2018**) but can be prevented by including ESG investments in the long term strategy of the companies

## Contribution

- ❑ Using a new loan level database to fill the gap on **credit risk assessment of green lending compared to other lending**

# Preview of results

- Companies with a better financial stance are more likely to take green loans
- Companies with green loans are less risky, **on average by 10 percent** in the matched sample. For the unmatched sample, the predictive PD rate is almost half compared to other loans.

*- Caution is required since we rely on a ex-post identified green loan database -*

- **From a policy perspective:**
  - Fostering green finance requires higher predictability of governments' decisions on the climate change agenda
  - Considering the long term horizon specific to the transition to a greener and low carbon economy, we conclude that microprudential authorities are better equipped to reach this purpose.

# Data

## New database on green loans

- *Green* loans granted by 13 Romanian banks (86% market share) to NFCs
- 5,1% of the total corporate portfolio granted between 2010-2020
- Firms with two loans (green and other loans) are considered just once, with the flag for green loans

## Databases used regularly for PD modelling

- Credit Register data with information on loan characteristics (around 1.4 million observations), including the *default* state
- Firms' financial statements at end-year

# Data

- Green loans *ex-post* identification: *loans granted for projects/ investments with the purpose of mitigating the impact of climate change or for the adaptation to climate change challenges.*

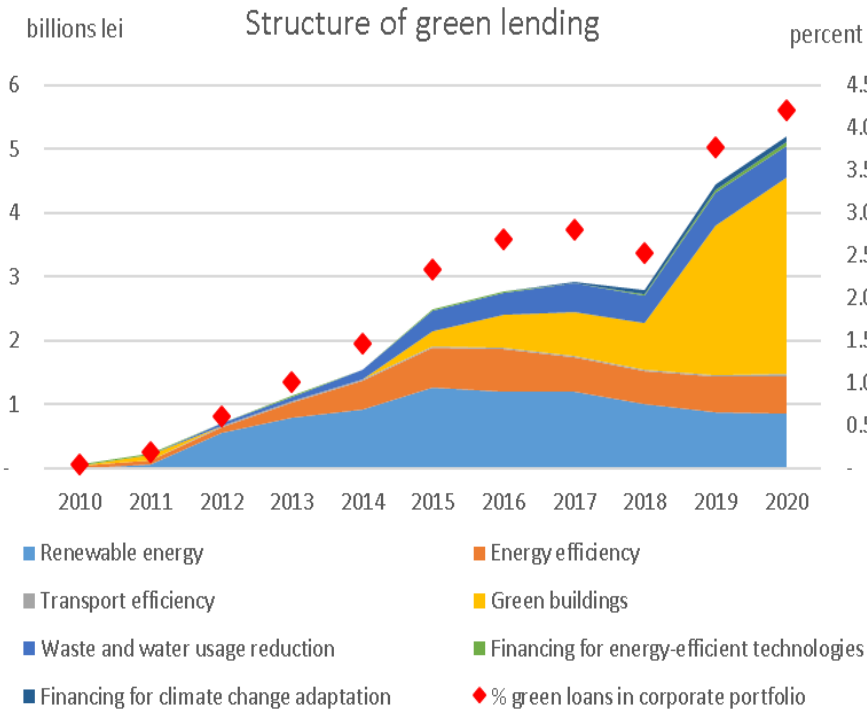
Categories of green activities* financed by banks:	
Renewable energy	Waste and water usage reduction
Energy efficiency	Energy-efficient technologies
Transport efficiency	Climate change adaptation
Green buildings	

\* based on the *Analysis of the NCMO Working Group on supporting green finance*



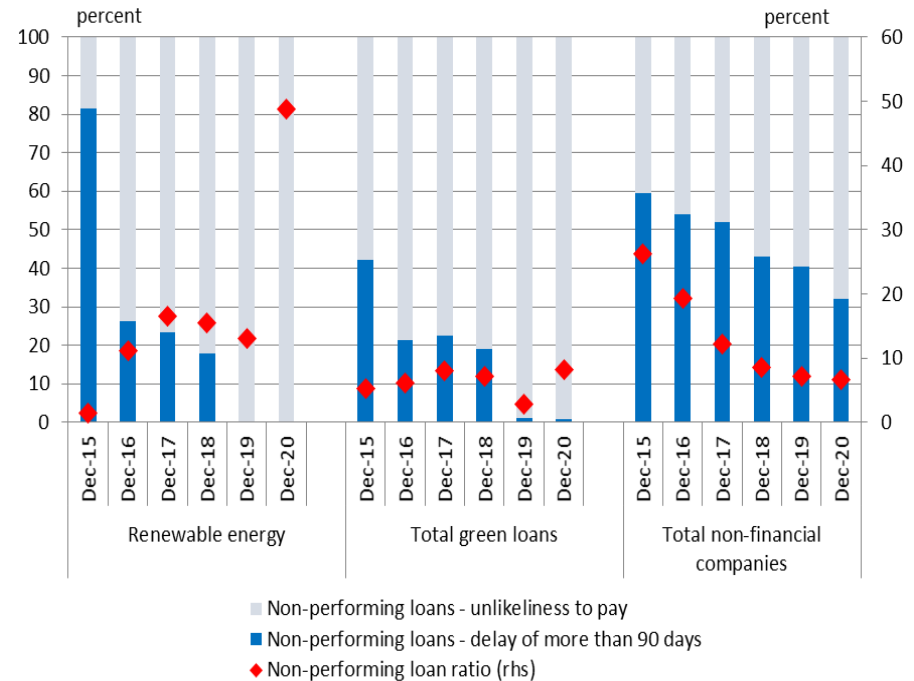
# Stylized facts

## Bank green loans to non-financial companies



Source: NBR, authors' calculations

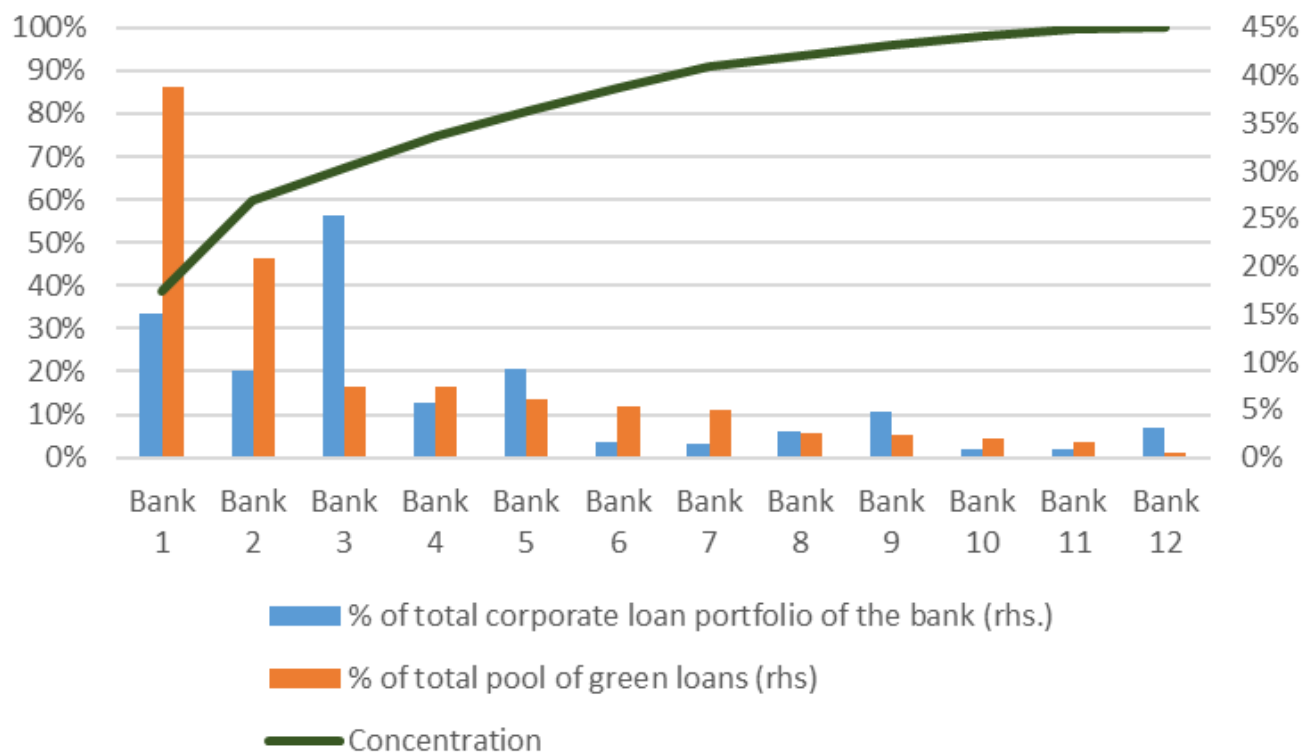
## Non-performing loan ratio\* of green loans



Source: NBR, authors' calculations  
\*according to EBA harmonised definition

# Stylized facts

## Concentration of green loans



Source: NBR, authors' calculations

# Methodology

Steps taken

1. Profile of firms taking a green loan

2. Probability of default model

3. Control for selection bias

*Penalized multivariate Logit model*

*Multivariate Logit model*

*Average treatment effects model*

**dependent variable:**  
*green loan dummy*

**dependent variable:**  
*default dummy*

1. Propensity score matching (PSM)  
2. Inverse-probability weighted regression adjustment (IPWRA)  
3. Augmented inverse-probability weighting (AIPW)

**explanatory variables:** financial soundness indicators, arrears, economic sector, FE

**explanatory variables:** financial soundness indicators, green loan dummy, FE

Variables and models

# Methodology

## i. The profile of firms taking green loans

$$\text{Logit}(P_{zt}(Y_{z,t} = 1 | x_1, x_2 \dots x_n)) = \alpha_z + \mathbf{x}'_{zt}\boldsymbol{\beta} + y_t + \varepsilon_{zt}$$

where:  $y_{zt}$  is *flag\_green*,  $P_{zt}$  is the probability of a firm to take a green loan,  $\mathbf{x}'_{zt}$  is a vector of explanatory variables for firm  $z$  at period  $t$  and  $\boldsymbol{\beta}$  the vector of coefficients,  $y_t$  are the fixed effects and  $\varepsilon_{zt}$  is the error term. All variables are included with a one year lag.

- We expect banks to behave differently depending on their portfolio structure, business strategies or board commitments
- The demand for a green loans is expected differ by economic sector
- Time effects account for the increase in preferences towards green projects/activities and macroeconomic developments
- Mean values of the coefficients based on a bootstrapping approach
- For robustness purposes we use a penalized *firthlogit* model

# Methodology

## ii. The credit risk model

$$\text{Logit}(P_{it}(Y_{i,t} = 1 | x_1, x_2 \dots x_n)) = \Phi_i + \text{Fin ind}_{i,z,t}\beta_1 + \text{flag\_green}_{i,t}\beta_2 + \varepsilon_{it}$$

where:  $y_{it}$  is the dependent variable (default flag) and  $P_{it}$  is the probability of a loan  $i$  to enter the default state at any moment in time  $t$ .

Financial indicators for the firm  $z$  that took the loan  $i$  are considered contemporaneous. The coefficient of interest is  $\beta_2$  and is expected to have a negative sign.

- ❑ Mean values of the coefficients based on a bootstrapping approach
- ❑ To account for a potential underestimation of the default rate, we estimate the default logit model only for loans with maturity before 2020 or for which the default is already observable.

# Results: The profile of firms taking green loans

	Full sample (2010-2020)			
	(1)	(2)	(3)	(4)
Fixed assets/ Total assets $t-1$	1.411*** (0.000)	1.439*** (0.000)	1.258*** (0.000)	1.251*** (0.000)
EBITDA/Sales $t-1$	0.518** (0.011)	0.580*** (0.001)	0.741*** (0.000)	0.727** (0.023)
Debt/Total assets $t-1$	-0.395** (0.016)	-0.460*** (0.001)	-0.324*** (0.004)	-0.352*** (0.009)
Non-bank arrears/ Total assets $t-1$	-1.492*** (0.000)			
Sales/Total assets $t-1$		-0.122 (0.107)	-0.092 (0.260)	-0.089 (0.155)
SME $t$			0.028 (0.92)	0.109 (0.76)
Corporation $t$			1.139*** (0.000)	1.197*** (0.002)
Private firm, domestic $t$				-0.172 (0.553)
Private firm, foreign $t$				0.395 (0.11)
Private firm, mixed $t$				-0.619 (0.254)
Sector & Bank & Time fixed effects	Yes	Yes	Yes	Yes
Observations	474 598	474 598	474 598	463 744
Pseudo R2	32.13%	32.02%	32.68%	32.73%
Accuracy ratio	81.9%	81.8%	82.8%	83.1%

Note: All estimations are carried using the data for the 13 reporting banks. For the logit model we use bootstrapping technique, with 100 repetitions. The values represent the coefficients and, in parentheses, the p-values: \* p<0.10, \*\* p<0.05, \*\*\* p<0.01

# Results: The profile of firms taking green loans

	Full sample (2010-2020)		2015-2020	
	(3)	(3 <sup>^</sup> )	(5)	(5 <sup>^</sup> )
Fixed assets/ Total assets <sub>t-1</sub>	1.258*** (0.000)	1.256*** (0.000)	1.216*** (0.000)	1.215*** (0.000)
EBITDA/Sales <sub>t-1</sub>	0.741*** (0.000)	0.739*** (0.000)	0.645*** (0.001)	0.644*** (0.001)
Debt/Total assets <sub>t-1</sub>	-0.324*** (0.004)	-0.320*** (0.000)	-0.200*** (0.004)	-0.195*** (0.003)
Non-bank arrears/ Total assets <sub>t-1</sub>				
Sales/Total assets <sub>t-1</sub>	-0.092 (0.260)	-0.091*** (0.004)	-0.131*** (0.000)	-0.130*** (0.000)
SME <sub>t</sub>	0.028 (0.92)	0.028 (0.88)	0.153 (0.72)	0.152 (0.45)
Corporation <sub>t</sub>	1.139*** (0.000)	1.138*** (0.000)	1.235*** (0.009)	1.233*** (0.001)
Sector & Bank & Time fixed effects	Yes	Yes	Yes	Yes
Observations	474 598	474 598	307 403	307 403
Pseudo R2	32.68%	-	33.22%	-
Accuracy ratio	82.8%	-	82.1%	-

<sup>^</sup> the estimation is done using the *firthlogit* approach.

# Results: The profile of firms taking green loans

- ❑ Firms with green loans tend to be in a superior financial standing: have higher profit margins, invest more, have a lower degree of indebtedness and are less prone to generate payment arrears to non-bank partners
- ❑ Corporations are more prone to access green loans compared to SMEs. Despite the increase in green lending after 2015, the SMEs access to green lending remains limited.
  - **Open Q:** *What will happen in the future?*
- ❑ Companies operating in the **mining**, trade and services sectors have a lower probability of accessing a green loan
- ❑ Results are stable over a shorter time span and under different specifications

**Take away:** *For now, companies that invest more are more concerned with their impact on climate and willing to invest for climate change adaptation purposes, as well as for diminishing their impact on climate change*



# Results: The credit risk model

	2010-2020			
	(1)	(2)	(3)	(4)
Fixed assets/ Total assets $_t$	-0.175*** (0.00)	0.906*** (0.00)	0.951*** (0.00)	0.931*** (0.00)
EBITDA/Sales $_t$	-1.138*** (0.00)	-2.025*** (0.00)	-1.813*** (0.00)	-2.106*** (0.00)
Debt/Total assets $_t$	0.818* (0.00)	0.362*** (0.01)	0.233*** (0.00)	0.389*** (0.00)
Flag green $_t$	-0.899* (0.10)	-0.814 (0.12)	-0.694 (0.13)	-0.786* (0.1)
Sales/Total assets $_t$	-1.749*** (0.00)			
ROA $_t$		-0.263*** (0.00)		
Arrears/Total assets $_t$			2.616*** (0.00)	
Corporates $_t$				-0.701*** (0.00)
Sector & Bank & Time fixed effects	Yes	Yes	Yes	Yes
No. obs	898 444	898 444	898 444	898 444
Pseudo R2	31.6%	19.82%	25.98%	19.95%
Accuracy ratio	76.9%	59.2%	66.0%	59.2%

Note: All estimations are carried using the data for the 13 reporting banks and for the loans for which we know the developments until maturity. The values represent the coefficients and, in parentheses the p-values: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

# Results: The credit risk model

	2010-2020	2015-2020
	(1)	(2)
Fixed assets/ Total assets $_t$	-0.159*** (0.00)	-0.108** (0.08)
EBITDA/Sales $_t$	-1.107*** (0.00)	-1.449*** (0.00)
Debt/Total assets $_t$	0.923*** (0.00)	0.789*** (0.00)
Flag green $_t$		-0.66* (0.09)
Sales/Total assets $_t$	-1.797*** (0.00)	-1.661*** (0.00)
Corporates with no GL $_t$	-0.495*** (0.00)	
SMEs with GL $_t$	-0.892*** (0.00)	
Corporates with GL $_t$	-1.554*** (0.00)	
Sector & Bank & Time fixed effects	Yes	Yes
No. obs	887 217	421 747
Pseudo R2	32,2%	31.99%
Accuracy ratio	77.4%	76.2%

Note: All estimations are carried using the data for the 13 reporting banks and for the loans for which we know the developments until maturity. The values represent the coefficients and, in parentheses the p-values: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ ; **GL** stands for green loans

# Results

- Average treatment effects -

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

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

All three approaches used for the treatment effect (PSM, AIPW and IPWRA) suggest that companies with green loans are less likely to default on their bank loans, on average by 10 percent

# Results

## – The credit risk model and the relevance of green loans -

- ❑ Over the cycle analysed, companies with green loans have a lower probability to enter default and the result holds over a smaller time-span
  - ❑ Firms with a better capacity to generate profits, improved efficiency in using the assets and lower degree of indebtedness have a lower probability to default on a loan.
  - ❑ Size of the firms matters: corporations generate less credit risk in banks' portfolios compared to SMEs. Although green lending increases at a larger pace after 2015 the SMEs access to it remains limited.
- *Open Q: Will the firms with green loans continue to bear less credit risk?*

# 5. Further improvements of the model

– Propensity score combined with exact matching -

**Scope:** Better selection of the control group: firms contracting loans other than green loans, within the same origination year and with similar propensity score

- ❑ Step 1. Estimate the propensity score based on one year behind financial data (firthlogit model); the score is based on firm level data
- ❑ Step 2. Winsorize – remove extreme values of the propensity score
- ❑ Step 3. Ranges for the exact matching - create bins for the financial variables, using T-1 financial statements
- ❑ Step 4. Propensity score matching (PSM) based on the propensity score and exact matching (financial information, firm size, economic sector)

Cross  
section,  
annual  
data

# 5. Further improvements of the model

–Reestimate the default logit model–

## II. Reestimate the default logit model

- Step 1. Create the panel database
- Step 2. Select a time horizon for observing the default
  - for eg. 3 year time horizon -
- Step 3. Reestimate the credit risk model
  - default = 90 days overdue payments-

Panel  
data

# 6. Conclusions

- ❑ For the period analyzed (2010-2020), green loans bear less credit risk compared with non-green loans.
- ❑ Financially sounder companies (with lower indebtedness levels and upper profit margin) are more likely to take green loans. However, we expect the future cycle to not look the same!
- ❑ Besides firms' financial characteristics, some other aspects specific for these firms with green projects **could** contribute to the lower PD: firms' governance or strategic planning for decarbonizing their activities
- ❑ From a financial stability perspective, microprudential supervision authorities are more equipped to react if material changes in legal framework for green projects would manifest. They could act via amendments to Pillar 2 requirements for green exposures, which ensures more flexible and timely reactions.

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Thank you!

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# Annex

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# National Committee for Macroprudential Oversight has issued recommendations with a view to support green finance

<http://www.cnsmro.ro/res/ups/Summary-Report-NCMO-green-finance.pdf>

## Objectives:

- A. To sustainably enhance access to finance for projects on the climate change agenda  
E.g.: Recommendations to banks and NBFIs to revisit (i) governance, (ii) strategy, (iii) risk management, (iv) scenario analysis and stress testing and (v) transparency, in order to take on board climate risk.

Institution responsible: NBR + Financial Supervisory Authority

- B. To support the structural change of the economy towards one with a higher value added

E.g.: Develop an industrial policy focusing on the climate change agenda, phased in gradually until 2025, in correlation with the European Commission's New Industrial Strategy for Europe

Institution responsible: Government (Ministry of Economy)

- C. To enhance transparency, improve the availability of information and raise awareness on the impact of climate change in society and the financial system

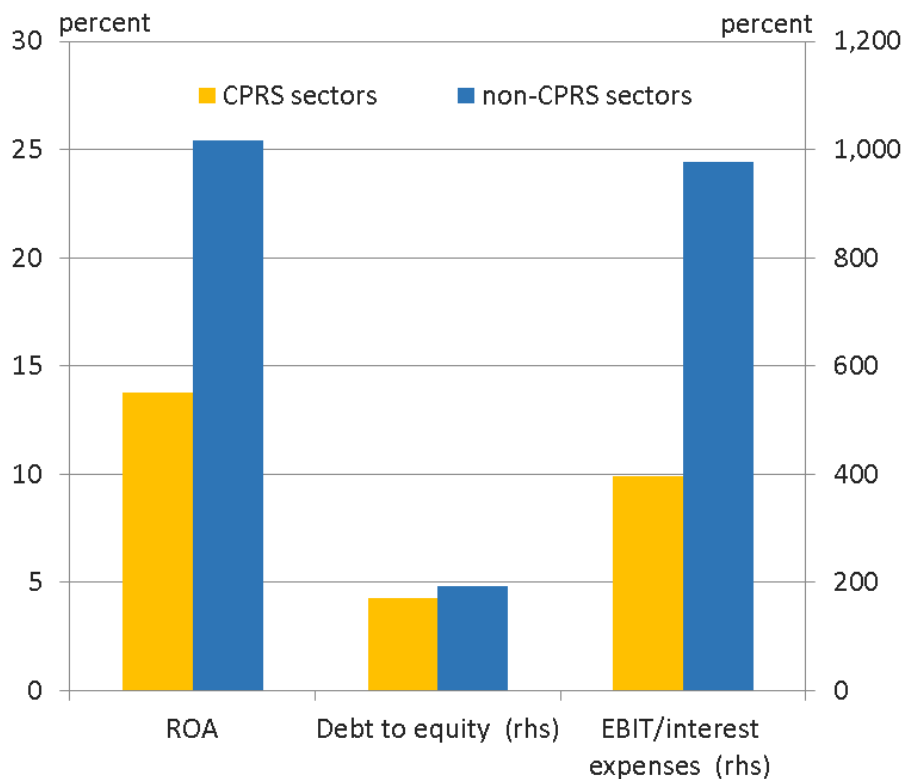
E.g.: Create a dashboard to monitor climate change risks to the banking sector; conduct annual stress tests on climate risk-related issues and publish the results

Institution responsible: NBR

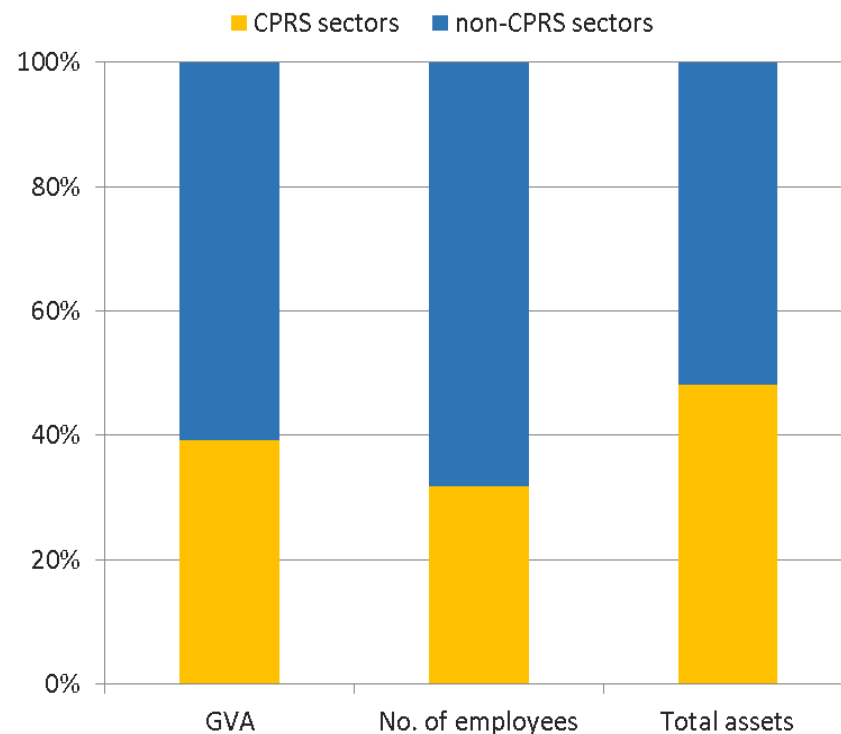
# Carbon intensive companies

Carbon-intensive companies have a significant share of the Romanian economy. They also hold the majority of assets, increasing the risk of stranded assets

### Financial soundness indicators



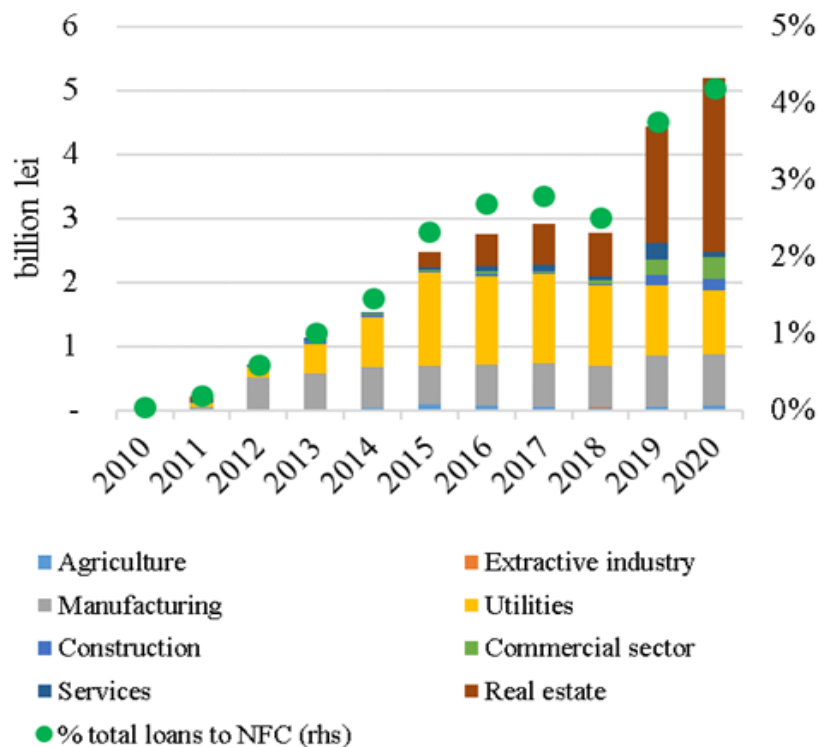
### Importance in overall economy



Source: MF, NBR calculations

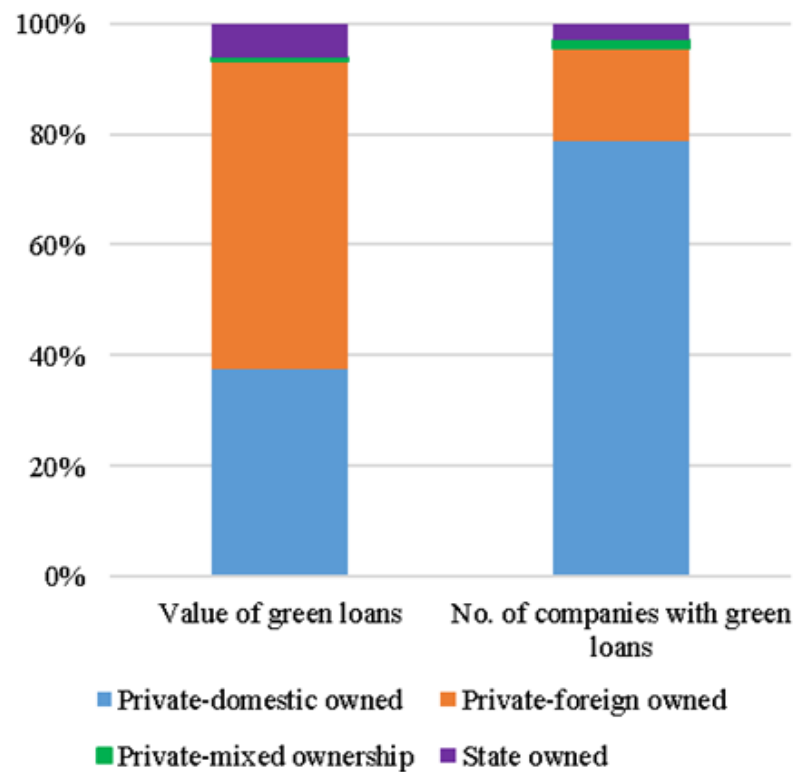
# Stylized facts

The structure of green lending by economic sectors



Source: NBR, authors' calculations

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



Source: NBR, authors' calculations

# Sources of data for PD modelling

