Climate and credit risk: the effect of carbon taxes on Italian banks' loan default rates*

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* The views expressed herein are those of the authors and do not necessarily represent the views of the Bank of Italy or the Eurosystem.

Overview

AIM: Estimate the effect of alternative carbon taxes on loan default rates at the sector level in the short term

How?

1. Select sectoral models: estimate the relationship between the default rates and the share of vulnerable firms/debt on historical data
   - Data on firms' vulnerability is obtained from the BdI micro-simulation model (De Socio et al., 2017)
2. Estimate default rates with alternative carbon taxes: exploit the sectoral models and data by Faiella et al. (2021) on firms' vulnerability with alternative carbon taxes
   1. **Faiella et al. (2021) estimate the energy demand of Italian firms** using granular administrative data
   2. Compute price variations of each energy fuel (electricity, heating and transport) for alternative carbon taxes
   3. **Simulate firms' energy expenditure, EBITDA with the alternative taxes**
   4. **Simulate the shares of vulnerable firms/debt with alternative taxes**, with the BdI micro-simulation model

Features?

- **Credit risks for firms**
- **Transition risks:** carbon taxes (€50, €100, €200 and €800 per ton of CO2)
- **Short-term partial equilibrium effect**

Advantages

Building on the micro-simulation model by Faiella et al. (2021) provides the following pros:

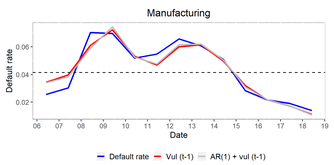
- Data:
  - **No reliance on GHG emission data:** avoid possible data quality issue
- Channel:
  - **Impact of climate policy shocks on firms' energy demand and cost structure:** heterogeneity within and across sectors
- Short horizon and partial equilibrium:
  - **One-off shock:** reduce modelling risk over longer time horizons and no dynamic balance sheet assumption
  - Simple but easily interpretable models and results

Motivating evidence

Why do we rely on firms' vulnerability to predict the default rates?

Example: Manufacturing

Target variable: default rate at the sector level



Model	Adj. R-sq.
AR(1)	0.672
AR(1)+$Vuln\,deb_{t-1}$	0.750
AR(1)+$rgdp\,gr_{t-1}$	0.723
AR(1)+$rgdp\,gr_{t-1}$+$Vuln\,deb_{t-1}$	0.782
AR(1)+VA_{t-1}	0.701
AR(1)+VA_{t-1}+$Vuln\,deb_{t-1}$	0.756

- **Positive and significant correlations (0-3 lags) between the share of vulnerable firms/debt and default rates at the sector level:** from 0.2 to 0.8
- **Share of vulnerable firms/debt anticipates the default rates at the sector level**
- **Simple models capture well the trend** of the default rates (the figure uses a MA(3))
- The share of vulnerable firms/debt **convey additional information beyond macro variables, sectoral value-added, and AR components** (see the table)
- True for all sectors except for Energy & Mining

⇒ Results by Faiella et al. (2021) are informative on the impact of alternative carbon taxes on Italian banks' default rates

Data

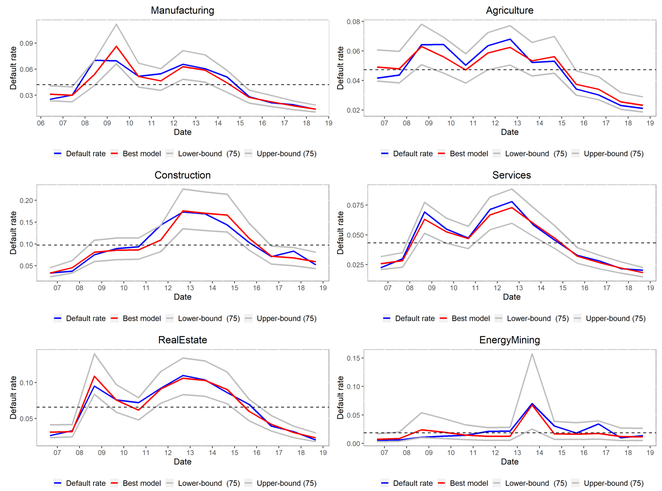
- Quartely data: DR, VUL, MACRO, VA
  - **Default rates (DR)** at the sector level (Italian Central Credit Registry)
  - **Share of vulnerable firms and debt (VUL)** at the sector level (BdI microsimulation model)
  - **Macro variables (MACRO)** common in scenarios (i.e. GDP gr, oil price, inflation rate, etc..)
  - **Sectoral value-added quarterly growth rate (VA)**
- From Q1 2006 to Q4 2019
  - Caveat: short time series
  - Linear interpolation of VUL to move from annual to quarterly data
- Sectors: Manufacturing, Agriculture, Construction, Services, Real estate, Energy & mining
  - Most exposed to transition risks (Battiston et al., 2017)

1) Models' selection: out-of sample forecasting excercise

- Target variable: default rate (DR)
  - Log-odd transformation (and linear models)
- Horizons (h): t+1, t+2, t+3, t+4
  - Direct forecast
  - Some tests on t+8, t+12
- For each sector (s) and horizon (h) we estimate more than 210 models:
  - AR(p) + MACRO (lags 1-3) + VA (lags 1-3) + VUL (lags 1-3)
- Rolling windows: T=R+P
  - R (in-sample) and P (out-of-sample)
  - First R: Q4 2014 (35 obs in- and 20 out-of-sample)
- For each h and s, we choose the model with min RMSE out-of-sample

Models' performance

Models selected for t+1: in-sample performance



- Similar plots up for all the horizons up to t+4
- Good out-of-sample predictive power for all sectors
- One exception is Energy and Mining
  - The default rates are highly volatile (small and concentrated sector)
  - We omit Energy and Mining from the analysis (it accounts for a small share of IT banks' loans).

2) Carbon tax: impact on default rates

Assume the Government introduced a carbon tax in 2018 and estimate the counterfactual default rates in 2019

- Estimates are based on the i) selected sectoral models and ii) simulated data provided by Faiella et al. (2021) on firms' vulnerability referred to 2018
- Alternative taxes: €50, €100, €200, and €800 per ton of CO2
  - €50-100 are values close to the price of emissions in the EU-ETS system until 2021
  - €200-800 are coherent to the NGFS a disorderly transition scenarios

Impact of a carbon tax over a 1-year horizon

Quarterly average default rates in 2019

		Manufact.	Agricul.	Construc.	Services	Real Estate	Tot.
No Tax		0.0144	0.0234	0.0596	0.0187	0.0232	0.028
50	Mean	0.0185	0.0325	0.0691	0.0297	0.0251	0.035
	Low 75	0.0137	0.0250	0.0502	0.0229	0.0194	
	High 75	0.0248	0.0421	0.0945	0.0385	0.0326	
	Mult. factor	1.2827	1.3841	1.1623	1.5913	1.0849	1.301
800	Mean	0.0263	0.0599	0.0687	0.0507	0.0252	0.046
	Low 75	0.0183	0.0380	0.0499	0.0347	0.0194	
	High 75	0.0376	0.0935	0.0939	0.0735	0.0326	
	Mult. factor	1.8269	2.5430	1.1557	2.7118	1.0861	1.865

- Credit risks for banks stemming from introducing a carbon tax during calm periods are modest in the short term
  - With a €50 tax in 2018, the quarterly default rate in 2019 increases by 1/4 (from 2.8 to 3.5 per cent)
  - Results are similar with a €100 or €200 tax
  - The effect increases with a €800 tax, but the default rates remain below the historical peaks
- The effect is heterogeneous across sectors
  - Agriculture and Services are the most affected sectors (less reactive to changes in energy prices)
  - The effect is smaller for Construction (which is the most sensitive to energy price changes)
- Results reflect economic conditions, Italian firms' financial position, and historically low default rates recorded in 2018: the impact could be more severe if the tax were applied to years with higher baseline default rates or more vulnerable firms.
- Results are robust to several tests
  - i.e. selecting alternative models/variables

Conclusions

- Novel methodology to estimate the effect of a carbon tax on banks' credit risk
- A carbon tax, in relatively calm times with low default rates, does not have a sizeable effect on the default rates at the sector level in the short term
- Possible next steps:
  - Medium-term or different phases of the financial cycle
  - Banks' credit losses
  - Other shocks with heterogeneous impacts across sectors (i.e. Covid-19, energy price, policy changes)

References

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