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Climate change and credit risk: The effect of carbon tax on Italian banks' business loan default rates[☆]

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Abstract

Climate change poses severe systemic risks to the financial sector through multiple transmission channels. In this paper, we estimate the potential impact of different carbon taxes (€50, €100, €200 and €800 per ton of CO2) on the Italian banks' default rates at the sector level in the short term using a counterfactual analysis. We build on the micro-founded climate stress test approach proposed by Faiella et al. (2022), which estimates the energy demand of Italian firms using granular data and simulates the effects of the alternative taxes on the share of financially vulnerable agents (and their debt). Credit risks stemming from the introduction of a carbon tax - during periods of low default rates - are modest for banks: on average, over a one-year horizon, the default rates of firms increase but remain below their historical averages. The effect is heterogeneous across different sectors and rises with the tax value; however, even assuming a tax of €800 per ton of CO2, the default rates are below their historical peaks.

JEL Classifications: Q43; Q48; Q58; G21

Keywords: Climate change; Carbon tax; Climate stress test; Banks' credit risk

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1. Introduction

Climate change poses systemic risks to the financial sector through multiple channels. Despite the growing literature analyzing the financial risks stemming from climate change, a better understanding of the transmission channels and the distributive effects across countries, sectors, and agents is still needed. We contribute to the flourishing literature on climate change and banking by proposing a novel methodology - based on firms' energy cost - to assess the impact of the energy transition on Italian banks' credit risk via the introduction of different carbon taxes on non-financial corporations (climate policy transition risk).[3] Understanding its potential impacts is essential to inform the heated debate on implementing a carbon tax, the implication for financial stability, and the possible prudential tools to address climate risks for the financial system.

We build on the micro-founded climate stress test proposed by Faiella et al. (2022), which simulates the effects of alternative carbon taxes (€50, €100, €200, and €800 per ton of CO2) on Italian firms' profits, the share of financially vulnerable firms and the debt held by them. The authors exploit firm-level administrative data to estimate the demand elasticity for different groups of firms, according to their sector. Then, they compute the price variations of each energy service (electricity, heating and transport) corresponding to the alternative taxes using the carbon emissions factors for each fuel. These variations are translated into sectoral policy shocks. Each group of firms indeed reacts to the price variations, according to its own energy mix and price sensitivity, changing the amount and the mix of the energy demanded. The new EBITDA, computed by taking into account the change in the simulated energy expenditure, is finally used as input into a micro-simulation model (De Socio & Michelangeli, 2017) to assess the financial vulnerability of Italian firms driven by the one-off introduction of a carbon tax. The authors estimate that the overall effect on financial vulnerability is small, but non negligible. With €50 carbon tax, the share of vulnerable firms and debt at risk would increase by about 45 and 11 per cent with respect to the baseline; the increase would be larger with a €200-€800 tax.[4]

Leveraging on their results on firms' vulnerability (our input), we estimate the potential impact of the different carbon taxes on Italian banks' default rates at the sector level in the short term. First, we combine three sets of historical data on: i) Italian banks' loan default rates at the sector level from the Italian Credit Register, ii) macroeconomic variables and iii) the share of financially vulnerable firms (and their debt) obtained from the micro-simulation model used to monitor financial stability at the Bank of Italy (De Socio & Michelangeli, 2017). We collect quarterly data from 2006 to 2019 for six sectors of economic activity (Manufacturing, Agriculture, Construction, Services, Real estate, Energy and Mining). Our empirical strategy is motivated by a strong positive correlation between the share of vulnerable firms (and their debt) and the default rates at the sector level, meaning that the former predicts well the latter in the short term and conveys additional information beyond macroeconomic and sectoral variables and autoregressive components. We thus select different sectoral models in which we predict the sectoral default rates as a function of the share of

[3] Transition risks are the risks that arise during the transition toward a low-carbon economy, these risks can result from policies, such as carbon taxes, but also technological or sentiment changes.

[4] With a €200 carbon tax the indicators would increase by 56 and 15 per cent respectively, while considering €800 carbon tax, the two indicators would rise by 92 and 24 per cent.

vulnerable firms (and debt). The models are selected according to their out-of-sample performance over a one-year horizon, using a standard forecasting exercise with rolling windows and direct forecast, where the target variable is the sectoral default rate. The evaluated models include autoregressive components, lags of the share of vulnerable firms (and debt), the real GDP (RGDP) growth rate and the sectoral value added growth rate. The selected models have a high predictive power over the short term. Finally, we assume that the Government implemented a carbon tax during 2018[5] and estimate the counterfactual default rates in 2019 using the selected sectoral models and the simulated shares of financially vulnerable firms and debt provided by Faiella et al. (2022).

Results show that the credit risks for Italian banks stemming from introducing a carbon tax - during a favorable financial cycle phase characterized by historically low banks' default rates - are modest in the short term. Assuming that the Government implemented a carbon tax of €50–200 during 2018, the quarterly default rates (for the sectors analysed) would increase in 2019 on average by 1.3 (or 1.4) times from 2.8 to 3.6 per cent, remaining, however, below their historical averages. The effect is heterogeneous across different sectors with agriculture and services being the most affected, consistently with the fact that these sectors' energy demand is less elastic with respect to price changes and therefore suffer the most from the introduction of a carbon tax.[6] The higher the value of the carbon tax, the higher the increase on default rates; still, even assuming a carbon tax of €800, the average quarterly default rate remains below the historical peak of about 9.5 per cent recorded in 2013.[7] The results reflect the economic conditions, the financial position of Italian firms and the historically low default rates recorded in 2018, suggesting that the impact could be more severe if the tax were applied to years with higher baseline default rates or weaker firms' financial conditions. Indeed, although the default rates remain low with a carbon tax between €50 and €200, the percentage change is not negligible, reaching high values for the most affected sectors (70 per cent for Services and 60 per cent for Agriculture). These results inform the discussion on the banking system's risks during the transition to a low-carbon economy. Although the estimated transition risks are overall small, they are not negligible. The effect of an increase in the energy price on the probability of default is non-linear and highly heterogeneous across sectors. Further, risks arise from a few sectors, not necessarily those with the highest emission intensity. Banks, therefore, must commit to evaluating and managing the risks in their portfolios. At the same time, supervisors should discuss the appropriate micro and macro-prudential tools to address climate-related financial risks for the banking system (ESRB, 2022), taking into account these findings.

Our work contributes to the literature also by suggesting a novel methodology to estimate the effect of alternative carbon taxes on the banks' credit risk that differs from the available macro-based climate stress tests in several dimensions and could be employed by other authorities.[8] First, building on Faiella et al. (2022), we consider the impact of the shock on the firms' cost structure, taking into account how their energy mix and demand adjust to energy price changes according to

[5] The choice of the period is driven by Faiella et al. (2022) which estimate the firms' financial vulnerability in 2018.

[6] According to Faiella et al. (2022), on average, a 1 per cent increase in energy prices reduces firms' energy demand by about 0.23 per cent points. Construction firms' energy demand is the most sensitive to price changes; on the contrary, fossil fuel demand in agriculture is inelastic. Services' energy demand is less reactive than industry, particularly for firms with more than 50 employees.

[7] This is the average default rate for the sectors considered in the analysis.

[8] For examples of the available climate stress test exercises, see Allen et al. (2020), ACPR (2020), Clerc et al. (2021), Vermeulen et al., (2018, 2019), BoE (2019, 2020, 2021), and Alogoskoufis et al. (2021).

the estimated elasticity. The energy-demand channel represents a key novelty of our approach relative to the existing analyses that instead use firms' greenhouse gas emissions (GHG) data - so-called scope 1, 2, and 3 emissions - as a proxy for the exposure to the transition risks.[9] Second, we do not rely on GHG data provided by external data providers and bypass the associated data quality issues. Third, we focus on the partial equilibrium effects of the climate shock in the short term (1 year), avoiding the typical very long-term horizons and the related modelling challenges (Baudino & Svoronos, 2021). The last one represents both a strength and a limitation of our approach. On one side, the proposed methodology allows us to obtain relatively transparent and interpretable estimates of the effect of a climate policy shock on the banking system in the short term. On the other side, this short-term partial equilibrium exercise neglects the impact on the aggregate economy, banks' reactions, and firms' adjustments over a more extended period. Future extensions of this work may consider a longer-term perspective (i.e. 3 or 5 years) to overcome this issue or different phases of the financial cycle characterized by a weaker firms' financial position and compute credit losses by applying the stressed default rates into a top-down stress test model.

Notably, the framework developed, which links the outcome of the microsimulation model proposed by De Socio and Michelangeli (2017) to the bank's default rate at the sector level, could be employed for several additional analyses. First, it allows for studying any energy price shocks. Second, it could be used, for instance, to run a fully-fledged stress test using the NGFS scenarios (NGFS, 2020, 2021a) or to study the effect of alternative exogenous shocks, such as Covid-19, regulatory or policy changes, and climate developments that may have heterogeneous impacts within and across sectors.

Finally, the methodology proposed can be adapted to the need of other European central banks or supervisors, which can access the Eurostat data to estimate the firms' energy demand, as described by Faiella et al. (2022), firms' balance sheets, and data on banks' exposures and firms' probability of default.

The paper proceeds as follows. Section 2 explains why studying the potential effect of a carbon tax is relevant to inform policymaker decisions. Section 3 presents our theoretical framework and methodological contribution. Section 4 describes the data and the empirical analysis. Section 5 discusses our main findings on the impact of alternative carbon taxes on the default rates, while Section 6 concludes.

2. Why looking at carbon taxation and the banking system?

According to the IPCC (2021) report, it is undeniable that human influence has warmed the atmosphere, ocean, and land. Global temperature will continue to increase until at least mid-century, and global warming of 1.5 °C and 2 °C (relative to the pre-industrial levels) will be exceeded during the 21st century unless deep reductions in CO_2 and other GHG emissions occur in the coming decades. Policymakers need to act urgently to mitigate climate change and thus reduce its damaging effects, including rising sea levels, coastal flooding, and more frequent extreme weather events. Actions to date have been inadequate to achieve the ambitious targets

[9] Scope 1 relates to direct emissions from the company's owned or controlled sources, mainly produced by manufacturing processes, transportation, and fugitive emissions. Scope 2 covers indirect emissions from the generation of electricity, steam, heating, and cooling. Scope 3 includes all other indirect emissions that result from the value chain. Large listed companies generally report scope 1 and 2 emissions in their carbon emission footprint disclosure. Scope 3 emissions are more complex to quantify and usually are not disclosed, posing significant challenges when comparing GHG intensities among companies.

of the 2015 Paris Agreement and the longer policies are delayed, the greater will be the cost of stabilizing global temperatures.

Fiscal policy has a crucial role to play in this battle. As argued by the IMF (2019) and many influential authors such as Tirole (2017), carbon taxes are among the most powerful tools to reduce fossil fuel emissions - although there are other efficient pricing tools such as emissions trading systems (ETS). By changing the relative prices among energy alternatives, carbon taxes correct the under-pricing of the externalities in the market and signal which inputs and products are more carbon-intensive (Nordhaus, 2019). Further, they foster innovation (Nordhaus, 2021) and provide incentives for firms and households to find the ways of reducing energy use, moving away from fossil-fuel technologies, and shifting toward cleaner alternatives. At the same time, they also generate public revenues (Hepburn et al., 2020) that can be used for public investment (i.e. in sectors that need large investment to de-carbonize) and to deliver recovery packages for those most affected by the higher cost of energy (i.e. low-income households). Although overall carbon taxes alone may not be enough alone, they will be an essential lever for most countries (Hepburn et al., 2020) which should not only establish policies that raise the price of emissions, but also take actions coordinated at the global level (see, for instance, Hepburn et al., 2020; McKibbin & Wilcoxen, 2009; Alestra et al., 2022).

Several countries in the European Union have already implemented carbon taxes using different schemes, such as Germany, France, and Denmark. Besides, carbon pricing is a pillar of the EU Green Deal to achieve climate neutrality in the EU by mid-century.[10] While Italy has not introduced such a tax yet, it is relevant to study the potential effects of its application, given the country's strong commitment to reducing GHG emissions.

Although there is a growing literature studying these issues (i.e., Metcalf & Stock, 2022), the effects of the implementation of a carbon tax on key socioeconomic and distributional outcomes (see Peñasco et al., 2021 for a recent review) and on financial stability are still partially uncovered. Decarbonizing the economy is expected to come at an economic cost, at least in the short run (Acemoglu et al., 2012); Nordhaus (2021). Depending on the policy choices, some of these costs will likely be borne by owners of financial assets, including banks, especially in the event of a disorderly green transition (ESRB, 2022; Scholtens and Goot, 2015; Smale et al., 2006). Higher prices on GHG emissions lead to additional costs for emission-intensive sectors; firms not able to adapt their production processes and decrease their emissions might be at higher risk of default, resulting in credit losses for exposed banks. These costs can be substantial and range across a wide variety of sectors (Campanale et al., 2011). This paper contributes to the debate by studying the impact of alternative carbon taxes on the banking sector and in particular on the business loans' default rates in Italy for different sectors. We aim to provide insights for policymakers on the implementation of carbon pricing reforms to achieve the objective of limiting the increase in global warming in accordance with the Paris goals. Results on the potential impact of these taxes on the different economic sectors is essential to decide how to calibrate and when to implement such policies, and possibly choose how to allocate the relative revenues. Importantly, our results will inform supervisory authorities on the possible effects for banks and thus the ongoing discussions on the developments of prudential policies to mitigate climate risks (ESRB, 2022).

[10] The European Green Deal requires to achieve climate neutrality by 2050 and expands the perimeter of carbon pricing, extending the coverage of the EU-ETS, introducing a carbon tax on non-ETS sectors and levying a Carbon Border Adjustment on imported goods of carbon-intensive sector. (https://ec.europa.eu/info/strategy/priorities-2019–2024/european-green-deal it).

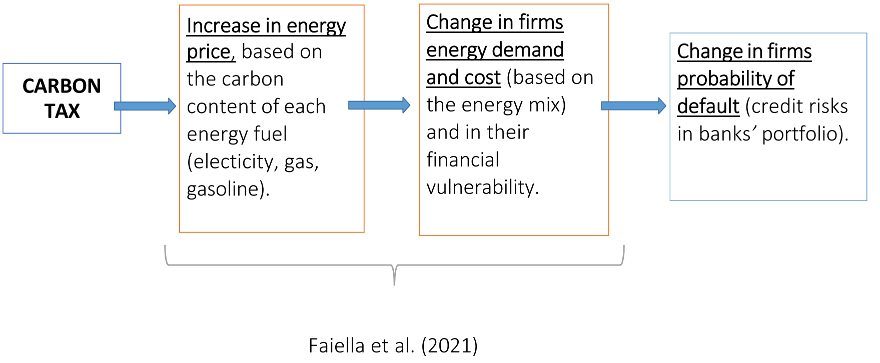

Figure 1. Energy-cost channel.

3. Theoretical framework

Several central banks are currently developing and running climate scenario analyses and stress test to assess physical and transition risks for the financial sector; among the others, some relevant examples are provided by Clerc et al. (2021), Allen et al. (2020), Alogoskoufis et al. (2021), BoE (2021), Vermeulen et al. (2019), ECB (2022), ESRB (2022) (for a review see NGFS, 2021b). These exercises differ in the scenarios, methodologies (top-down vs. bottom-up), underlying data (firm-level or sector-level data), and the horizon of the analysis (up to 30 years). Most of these works employ climate scenarios (such as those provided by the NGFS), look at short (3–5 years) and long-term horizons (up to 30 years), and use data on emissions as a proxy of the exposure to the transition risk of each firm or sector.

We contribute to this literature by looking at a different perspective. We assume a climate shock triggered by the imposition of a one-off (unexpected) carbon tax on final energy uses and study its effect on banks in the short term (1 year), as described in Fig. 1. Building on Faiella et al. (2022), rather than using emission data as a proxy of the exposure to transition risks, we exploit the increase in firms' cost structure due to the introduction of the carbon tax. Precisely, Faiella et al. (2022), first, compute the increase in energy prices based on the carbon content of each energy fuel (electricity, gas, and gasoline). Second, they measure firms' elasticity of demand using balance sheet data (sourced from Cerved) integrated with firm-level energy demand[11] and simulate the change in the firms' energy demand and costs with alternative carbon taxes, according to their elasticity of demand and energy mix. Finally, they evaluate how the change in energy expenditure affects firms' financial vulnerability by leveraging on the micro-simulation model proposed by De Socio and Michelangeli (2017). According to this model, vulnerable firms are those whose gross operating income is negative or whose net interest expense ratio to gross operating income exceeds 50 per cent.

In this paper, we exploit the estimates of firms' financial vulnerability in the presence of a carbon tax provided by Faiella et al. (2022) to assess how the tax affects firms' probability of default in the different economic sectors from the banking perspective, as described in the

[11] The firm-level energy demand is imputed for several fuels using Eurostat industry-level data on firms' energy use per employee together with INPS firm-level information on employees.

following sections. The choice to rely on the energy-cost transmission channel proposed by Faiella et al. (2022) is a novelty of our work and allows us to directly account for the impact that the increase in energy price would have on firms depending on their demand sensitivity and energy mix, in a partial equilibrium and static framework.

4. Empirical analysis

4.1. Data

The data integrates three different sets of information for the period from March 2006 until December 2019. We first collect quarterly seasonally adjusted data on Italian banks' default rates from the Italian Central Credit Register at the sector level.[12] This dataset comprises information at the firm level that we aggregate to obtain sectoral data. For the scope of the analysis and coherently with literature, we consider the sectors that are the most exposed towards transition risk (Battiston et al., 2017): Manufacturing, Agriculture, Construction, Services, Real Estate, and Energy and Mining.[13] Second, we collect data on the share of financially vulnerable firms (and their debt) obtained from the micro-simulation model used to monitor financial stability at the Bank of Italy (De Socio & Michelangeli, 2017) and computed as the fraction of firms that are vulnerable within each sector. These are annual data at the sector level for which we employ the same classifications used for the default rates. As these shares are not available quarterly, we linearly interpolate the annual data to obtain quarterly data. Finally, we employ quarterly data on several macro variables that feed into the Bank of Italy stress test model (e.g. GDP, oil price, inflation, interbank interest rates, etc.) and the sectoral value-added quarterly growth rate as a complement. These variables are meant to capture the overall economic cycle and sectoral dynamics.

We report the main descriptive statistics in Appendix. The data are heterogeneous across sectors: the default rates are on average higher for Construction and Real Estate due to some high values recorded between 2012 and 2015, while the share of vulnerable firms and debt are larger for Construction and Agriculture. Notably, for Energy and Mining, the data are volatile over time and the default rates range from 0.2 per cent in Q2 2006 to 23.3 per cent in Q4 2013. The peak observed at the end of December 2013 is due to the default of a large firm; excluding this outlier, the data still ranges from 0.2 per cent to 6.1 per cent.

4.2. Empirical motivation

Our empirical strategy is motivated by the significant positive pairwise correlation between the banks' loan default rates and the share of vulnerable firms (debt) at the sector level (Table 1), although there are differences in the magnitudes across sectors. The contemporaneous correlations range between 0.2 and 0.8: they are higher for the Manufacturing industry and lower for Energy and Mining. The raw correlations also show that the share of vulnerable firms (and debt) predicts well the default rate from 1 to 3 quarters ahead. Notably, very simple univariate models

[12] A ratio represents the default rate of loans in a given quarter. The numerator is the amount of defaulted loans during the quarter. The denominator is the amount of performing loans at the end of the previous quarter. This is the definition of adjusted defaulted loans adopted at the Bank of Italy, into force in March 2006.

[13] These are classified according to the European Community (NACE) sectoral classification.

Table 1
Correlations.

	Default rate					
	Manuf.	Agricul	Constr	Services	Real Est.	Ener. & Min.
Share of vuln. firms	0.812	0.610	0.416	0.679	0.568	0.167
Share of vuln. debt	0.759	0.623	0.494	0.490	0.337	0.300

Note: Contemporaneous correlations at the sector level.

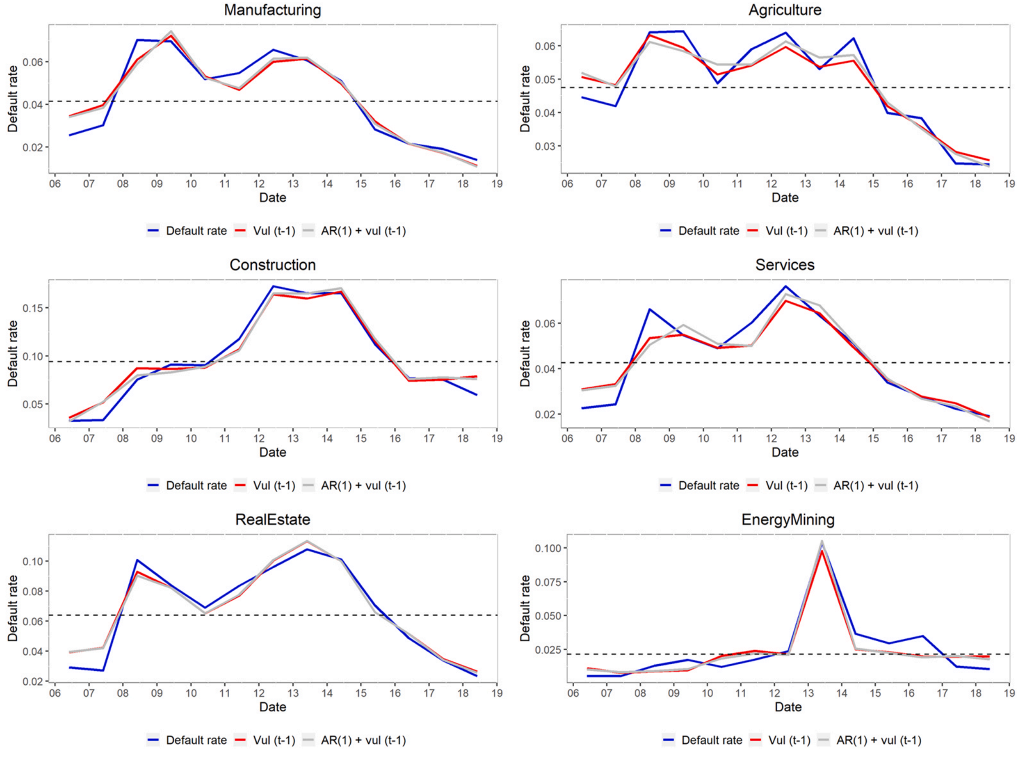

Figure 2. In sample explanatory power of the share of vulnerable firms.
Note: The blue line displays the actual default data. The red lines display the default rates predicted using the following univariate model $Def.rates_t = \alpha + \beta * V\ uln.deb_{t-1} + e_t$. The grey lines display the default rates predicted using the following univariate model $Def.rates_t = \alpha + \rho Def.rates_{t-1} + \beta *, Vuln.deb_{t-1} + e_t$. $Def.rates_t$ is the sectoral default rate, and $Vuln.deb_{t-1}$ is the share of vulnerable debt for the same sector one quarter in advance. For Energy and Mining the specifications include a dummy for Q4 2013, otherwise the Adjusted R-squared are very close to zero. In the figure the data are smoothed with a 3 quarters moving average.

that include as regressors only the lagged share of vulnerable debt (or firms) capture well the dynamics of the default rate (Fig. 2).[14] Furthermore, including the share of vulnerable debt helps improving the explanatory power on the sectoral default rates of alternative benchmark

[14] Note that such simple models do not capture some intra-annual peaks that instead can be captured, including additional controls such as the real GDP growth rate and autoregressive components.

Table 2
In sample explanatory power of the share of vulnerable firms.

Model	Adj. R-sq.					
	Manuf	Agric	Const	Serv	R. Est.	Ener. & Min.
AR(1)	0.672	0.637	0.724	0.688	0.745	0.843
AR(1) + $Vuln.\ deb_{t-1}$	0.750	0.680	0.744	0.724	0.770	0.865
AR(1) + $RGDP\ gr_{t-1}$	0.723	0.643	0.725	0.780	0.756	0.840
AR(1) + $RGDP\ gr_{t-1}$ + $Vuln.\ deb_{t-1}$	0.782	0.677	0.739	0.785	0.768	0.864
AR(1) + Va_{t-1}	0.702	0.638	0.730	0.738	0.743	0.850
AR(1) + Va_{t-1} + $Vuln.\ deb_{t-1}$	0.756	0.760	0.741	0.833	0.765	0.873

Note: Adjusted R-squared from the estimated models where the dependent variable is the default rate at time t. $Vuln.deb_{t-1}$ is the share of vulnerable debt for the same sector one quarter in advance. $RGDP$ gr_{t-1} is the RGDP growth rate at t-1 and Va_{t-1} is sectoral value-added one quarter in advance. For Energy and Mining the specifications include a dummy for Q4 2013, otherwise the Adjusted R-squared are very close to zero.

models substantially, proving that they convey additional information beyond macroeconomic variables and lagged values of the default rates (Table 2).

This first piece of evidence motivates our approach by suggesting that the shares of vulnerable firms (and debt) are good predictors of the sectoral default rates in the short-term and hence that the results provided by Faiella et al. (2022) can be informative to estimate the impact of alternative carbon taxes on the Italian banks' default rates.

4.3. Models' performance and selection

To select the sectoral models, we run a standard out-of-sample forecasting exercise with direct forecasts from 1 up to 4 quarters ahead, where the target variable is the default rate.[15]

For each sector and horizon, we compare more than 210 models that include autoregressive components (until order 3), lags of vulnerable firms and debt share, lags of the real GDP growth rate, and/or lags of the sectoral value added.[16] We consider up to 3 lags of the regressors given the shortness of our sample. Among the macro-economic variables, we only focus on the real GDP growth rate since the in-sample analysis shows that adding other ones variables to the models does not improve the explanatory power once we condition on lags of the real GDP growth rate, of the dependent variable and the share of vulnerable firms (or debt). We use a recursive (expanding) windows scheme in the following way. We start by splitting the sample into two partitions: D1 (in-sample) and D2 (out-of-sample). Our first in-sample consists of 35 observations from Q1 2006 until Q4 2014, while the out-of-sample includes the residual observations. We estimate each model on D1 (in-sample) and predict the default rates on D2 (out-of-sample). We then recursively include an additional quarter in D1 and shrink D2 until the end of our sample Q4 2019. For each sector and horizon, we select the model with the best out-of-sample performance, i.e. the minimum Root Mean Square Error (RMSE).

Since the default rate (Def_t) is a fractional variable that takes values in the unit interval [0;1], we estimate the models using a log-odds transformation (Wooldridge, 2010) such that the

[15] We also predict at 8 and 12 quarters ahead; however, we do not focus on long-term results given the partial and static nature of our exercise.

[16] As the maximum historical value for Energy and Mining series is an outlier, for this sector, we considered a dummy variable in the models, that is equal to 1 in Q4 2013 0 and 0 in the other quarters.

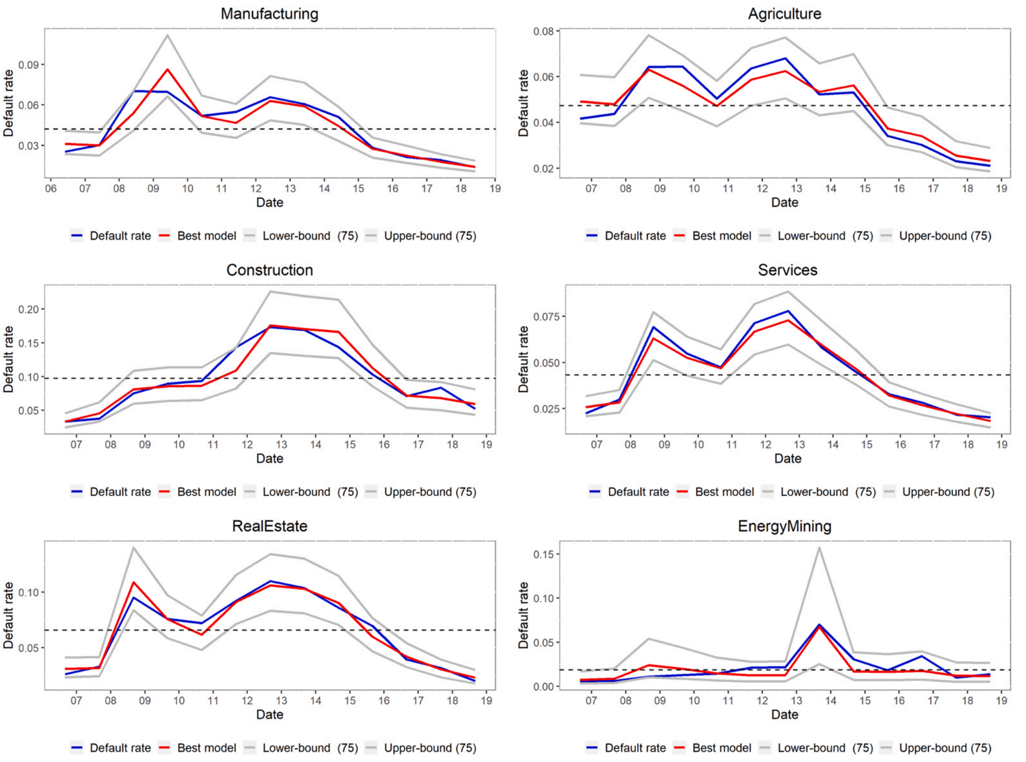

Figure 3. Models selected for t + 1: in-sample performance.
Note: The blue line displays the actual default data. The red lines display the fitted values estimated (in-sample) using the sectoral models selected with the forecasting exercises. The grey lines are the 75 per cent confidence intervals. For Energy and Mining the specifications include a dummy for Q4 2013. In the figure, the data are smoothed with a 3 quarters moving average.

dependent variable is $log(Def_t/(1 - Def_t))$.[17] We also estimate all the models using a linear specification (i.e. where the dependent variable is the default rate): the performance obtained with these two alternative specifications are very similar in terms of fit.[18]

Fig. 3 illustrates the in-sample fit of the selected models for 1 quarter ahead. In Table 3 we also report the estimates for the same models. Similar figures and tables are available for the other time horizons. The models capture well the dynamics of the actual default rates for all sectors, except for Energy and Mining. For the latter, indeed, the selected model's explanatory power is much lower than the one observed for the other sectors (the in-sample adjusted R-squared is about 0.5 versus 0.8) and is driven by the macroeconomic variables (i.e. RGDP growth). This result is due to the fact that the default rates vary substantially around values very

[17] Precisely, we assume that the log-odds transformation yields a linear model with an additive error independent of x, so that $log(Def_t/(1 - Def_t)) = x\beta + e_t$ and $E(e_t x) = E(x)$.

[18] A first difference model specification (i.e. where the dependent variable is $(Def_t - Def_{t-1})$) does not improve the forecast performance.

Table 3
Sectoral models for t+1.

	Manufacturing	Agriculture	Construction	Services	Real Estate	Energy & Mining
			Default rate			
Def rates$_{t-1}$	0.243*	0.462***	0.248*	0.290**	0.608***	-0.065
Def rates$_{t-2}$	(0.143)	(0.136)	(0.137)	(0.112)	(0.144)	(0.131)
	0.079	0.423***	0.203	0.419***	-0.188	
Def rates$_{t-3}$	(0.141)	(0.141)	(0.135)	(0.102)	(0.156)	
	0.267**		0.368***		0.469***	
Vuln debt$_{t-1}$	(0.124)		(0.128)		(0.154)	
			4.161***			
Vul$_{t-1}$	5.497***	17.557**	(1.079)	4.477***		
Vul$_{t-2}$	(1.414)	(7.433)		(1.159)		14.051
		16.069**				
Vul$_{t-3}$		(7.765)				(17.936)
						-15.169
Vuln debt$_{t-3}$					1.803**	(18.782)
RGDP gr$_{t-1}$					(0.705)	-21.688
					-19.383***	
RGDP gr$_{t-1}$					(6.191)	(12.987)
						-0.0001***
Va$_{t-1}$		0.954		-23.483***		(0.00001)
Va$_{t-2}$		(1.296)		(5.819)	1.878	
Va$_{t-3}$	-1.798		0.245		(5.674)	-0.256
	(1.509)		(1.781)			(0.595)
Constant	-2.739***	-1.017	-2.998***	-2.276***	-0.922***	17.834***
	(0.670)	(0.711)	(0.727)	(0.522)	(0.324)	(5.148)
Observations	52	52	52	52	52	52
Adjusted R^2	0.852	0.792	0.813	0.886	0.875	0.560

Note: Selected models for 1 quarter ahead. The dependent variable is the log-odd transformation of the default rate. $log(Def_t/(1-Def_t))$, where Def_t is the default rate at time t. Also the autoregressive components are transformed. Vul_t is the share of vulnerable firms, while $Vul\ debt_t$ is the share of vulnerable debt. $RGDPgr_t$ is the real GDP growth rate. Va_t is sectoral value-added. The model for Energy and Mining includes a dummy for 2013Q4. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

close to zero as this is a small sector populated by a few, primarily large, firms. In the next section, hence, we abstract from this sector given the lack of robustness of the results. Note that, despite the relevance of this sector in the transition to a greener economy, it represents only a small part of the Italian banks' balance sheet exposure and therefore can be omitted at this stage.[19]

5. Results: the impact of alternative carbon taxes on sectoral default rates

We assume that the Government in 2018 introduced a carbon tax and we estimate the counterfactual default rates in 2019 by using the selected sectoral models and the simulated data provided by

[19] Italian banks' loans to non-financial corporations are concentrated in a few counterparty sectors. As of December 2020, Services represented around 50 per cent of total gross performing loans, followed by Manufacturing (30 per cent) and Construction (8 per cent). Energy and Mining represents around 3 per cent.

Faiella et al. (2022) on the share of financially vulnerable firms and debt with alternative carbon taxes in 2018, corresponding to €50, €100, €200, and €800 per ton of CO2 (see the Appendix for the estimates by Faiella et al. (2022)). We assess the effects on the default rates in the 2019 as the counterfactual data provided by Faiella et al. (2022) refer to 2018 and we aim to study the effect of the taxation in the short term, given the static and partial nature of the exercise.

We consider alternative values for the tax since despite the widespread agreement on the efficacy of these tools, it's still unclear which should be the correct level of the tax to achieve the climate targets, and several estimates exist depending on the assumptions and models used (Gollier, 2022). As discussed in Faiella et al. (2022), the values of the carbon taxes are chosen such that €50–100 per ton of CO2 are values close to the price of emissions in the EU-ETS system,[20] while €200–800 correspond to the value of the social cost of carbon in the event of a disorderly transition[21] as in the NGFS scenarios (NGFS, 2021a). As explained in Faiella et al. (2022), using 2018 prices as the baseline, the introduction of a carbon tax of €50 per ton is equivalent to adding a surcharge of €0.014 to each kWh of electricity (+6 per cent), €2.8 to each GJ of gas (+12 per cent) and €0.12 to each litre of gasoline or gasoil (+8 per cent). For firms, the implied cost variations range from 15 per cent (for a €50 tax) to 230 per cent (for an €800 tax).

In Table 4, we report the estimated impact on the default rates. Results show that the credit risks for banks stemming from introducing a carbon tax during calm periods are modest in the short-term. Assuming that the Government implemented a carbon tax of €50 during 2018, the quarterly average default rates in 2019 would increase by 1.3 times compared to the case in which we assume no taxes (from 2.8 to 3.6 per cent). For each sector, the stressed values remain below the historical average and differ statistically from the baseline rate only for the two most affected sectors (Agriculture and Services).[22] As observed in Faiella et al. (2022), similar results are obtained when assuming a carbon tax of €100 or €200 suggesting that a €50 tax is sufficient to increase the probability of default of the most vulnerable firms, while financially solid firms are not highly affected by taxes in the range between €50 and €200. The effect increases assuming a carbon tax of €800, when the quarterly average default rate increases by 1.86 times, although it still remains below the historical peaks for all the sectors. In this case, the increase from the benchmark with no taxes is significant for all the sectors.

The results reflect the economic conditions (characterized by low interest rates), the Italian firms' financial position, and the historically low default rates recorded in 2018, suggesting that the impact could be more severe if the tax were applied to years with higher baseline default rates or more vulnerable firms. Indeed, although the default rates remain small even when assuming a carbon tax of €200, the percentage change is not negligible.

The effect is heterogeneous across sectors, with Agriculture and Services being the most affected. According to Faiella et al. (2022), these sectors are less reactive to changes in energy prices and hence suffer a larger increase in the energy expenditure.[23] The default rate for Agriculture increases from 2.3 per cent to 3.2 per cent with a €50 tax and to 6 per cent with an €800 tax, while for Services it jumps from 1.9 per cent to 3.1 per cent with a €50 tax and to 5.1

[20] Since June 2021 the price of emissions allowances has been firmly above €50, progressively increasing to €85 at the end of the year.
[21] The policies for the transition are postponed and when the process of reducing esmission starts, it requires draconian measures as there are only a couple of decades left to achieve net zero.
[22] Note that we obtain large confidence intervals due to the shortness of our series.
[23] Firms' energy demand elasticity depends on their ability to change the overall quantity of energy demanded and their ability to adjust their energy mix moving towards fuels with a lower carbon emissions footprint.

Table 4
Impact of a carbon tax over a 1-year horizon.

		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
100 €	Mean	0.0191	0.0339	0.0693	0.0306	0.0252	0.036
	Low 75	0.0141	0.0258	0.0504	0.0235	0.0194	
	High 75	0.0257	0.0445	0.0947	0.0399	0.0326	
	Mult. factor	1.3248	1.4459	1.1656	1.6407	1.0864	1.333
200 €	Mean	0.0204	0.0369	0.0697	0.033	0.0252	0.037
	Low 75	0.0149	0.0274	0.0506	0.0250	0.0194	
	High 75	0.0277	0.0496	0.0952	0.0436	0.0326	
	Mult. factor	1.4160	1.5726	1.1712	1.7686	1.0861	1.403
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

Note: Annual average of quarterly default rates in 2019. The values with no taxes are estimated using the same models employed to estimate the counterfactual values assuming the introduction of the carbon taxes. These are very close to the actual values recorded in 2019. Low 75 and High 75 indicate the lower and the upper bounds for the 75 percent of the confidence intervals. The multiplicative factor shows how much the default rates increase with the tax relative to the no-tax case (i.e. 1.2 means it would increase by 1.2 times). Tot. is the average value over the sectors.

per cent with an €800 tax. The effect is smaller for the Construction sector, which historically recorded higher default rates but is the most sensitive to energy price changes and therefore only marginally affected by the introduction of a carbon tax.[24]

Results are robust when we consider different specifications, for instance, when excluding the real GPD growth rate and the growth rate of the sectoral value added or selecting alternative models that perform well out-of-sample (i.e. the best four models for each sector and horizon).[25] Results are also qualitatively similar when considering a linear specification (i.e. where the dependent variable is the default rate), although some differences exist in a few sectors.[26]

6. Conclusions and policy implications

Carbon taxation is one of the most likely and effective climate policy tools to reduce GHG emissions (Tirole, 2017). Despite the widespread agreement on its effectiveness, the debate on

[24] This result is due to the fact that Faiella et al. (2022) consider a partial equilibrium model where firms react to the carbon tax only by revising their demand for energy without taking any other action that might change their revenues.
[25] When we exclude the sectoral value-added, the impact for Agriculture is lower; with a €50 tax, the default rate increases to 2.9 per cent, while with €800 to 3.7 per cent.
[26] With the linear specification, the impact is slightly larger: with a €50 tax, the default rates would increase on average 1.48 times.

its potential implications for different sectors, economic agents, and the financial system is still open.

We contribute to this discussion by suggesting a novel methodology to estimate the effect of alternative carbon taxes on banks' credit risk and applying it to Italian banks. We find that the introduction of different carbon taxes within the range of €50–200 per ton of CO_2, in relatively quiet times with low default rates, does not have a sizeable effect on the default rates at the sector level in the short-term. The impact of an €800 carbon tax would be more considerable but still contained. The effect could be more severe if the tax is applied during years with higher baseline default rates or different phases of the financial cycle. Further, we show that the effect of an increase in energy prices on the default rates is not linear and highly heterogeneous across sectors. Notably, the sectors most affected are not necessary those characterized by higher carbon-intensity, but are those less reactive to energy price changes.

Policymakers must consider these new elements when choosing if, when, and how to calibrate such tax. Importantly, these findings also highlight the need to monitor the financial risks deriving from the transition to a low-carbon economy, which are still not entirely considered in the banks' risk management frameworks, as proved by the cli- mate stress test conducted by the ECB (ECB, 2022). At the same time, policymakers should also be aware of these risks and evaluate potential micro and macro-prudential measures to mitigate the financial impact of climate change (as discussed by the ESRB (ESRB, 2022)), taking into account the heterogeneity across and within sectors.

The present work opens avenues for future research in this progressive field. First, future extensions of this paper will consider a medium-term perspective (i.e. 3 or 5 years) or different phases of the financial cycle characterized by a weaker firms' financial position or higher default rates. Second, future analysis will compute credit losses by applying the stressed default rates to individual banks' transition matrixes and credit exposures into a top-down stress test model. Finally, the developed methodology can be employed to study the effect of alternative shocks characterized by non-linearity, such as those arising from Covid-19, energy price, regulatory or policy changes, and climate developments that may have heterogeneous impacts within and across sectors.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jpolmod.2022.11.007.

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