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CLIMATE CHANGE AND CREDIT RISK: THE EFFECT OF CARBON TAXES ON ITALIAN BANKS' BUSINESS LOAN DEFAULT RATES

by Maria Alessia Aiello* and Cristina Angelico+

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. (2021), 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 Classification: Q43, Q48, Q58, G21.

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

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1 Introduction[1]

Climate change poses systemic risks upon the financial sector through multiple transmission 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. To this aim, this study assesses the impact of the energy transition on the Italian banks' credit risk (*transition risk*) via the introduction of different carbon taxes (*climate policy shock*) on non-financial corporations.

We build on the micro-founded climate stress test proposed by Faiella et al. (2021), 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 (sourced from Cerved), integrated with firm-level energy demand,[2] to estimate the demand elasticity for different groups of firms, according to their size and sector. Then, they compute the price variations of each energy fuel (electricity, heating and transport) corresponding to the alternative taxes using the carbon emissions factors for each fuel. These variations are then translated into sectoral policy shocks. Each group of firms indeed reacts to the price variations, according to its own energy mix and price sensitivities, 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 and 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.[3]

Leveraging on their results (our input), we estimate the potential impact of the different carbon taxes on the Italian banks' default rates at the sector level in the short term. First, we combine three sets of historical data on: i) banks' credit quality – gauged by loan default rates at the sector level –, ii) macroeconomic variables and iii) the share of financially vulnerable firms (and their debt) obtained from the micro-simulation

[1]We would like to thanks Marcello Bofondi, Alessio De Vincenzo, Antonio Di Cesare, Ivan Faiella and Bruna Szego for thier useful comments and suggestions. The views expressed herein are those of the authors and do not necessarily represent the views of the Bank of Italy or the Eurosystem. All remaining errors are our own. Authors' emails: M. A. Aiello (Mariaalessia.Aiello@bancaditalia.it) and C. Angelico (cristina.angelico@bancaditalia.it).

[2]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.

[3]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.

model used to monitor financial stability at the Bank of Italy (De Socio and 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). We find 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. Second, we estimate the relationship between the default rates and the share of vulnerable firms (and debt) on the collected data for each sector. We adopt a standard out-of-sample forecasting exercise with rolling windows and direct forecast, where the target variable is the sectoral default rate. We evaluate multiple sets of models and select the ones with the best out-of-sample performance over a one-year horizon. 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. Finally, we assume that the Government implemented a carbon tax during 2018[4] 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. (2021).

Results show that the credit risks for the 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 firms 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.[5] 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.[6] 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

[4]The choice of the period is driven by Faiella et al. (2021) which estimate the firms' financial vulnerability in 2018.

[5]According to Faiella et al. (2021), on average, a 1 percent increase in energy prices reduces firms' energy demand by about 0.23 percentage 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.

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

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% for Services and 60% for Agriculture).

Our work suggests 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.[7] First, building on Faiella et al. (2021), 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 the estimated sectoral elasticity. Second, we do not rely on greenhouse gases emissions (GHG) - so-called scope 1, 2 and 3 emissions - provided by external data providers and bypass the associated data quality issues.[8] 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 and 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. For instance, it could be used to run a fully-fledged stress test using the NGFS scenarios (NGFS, 2020; 2021) or to study the effect of alternative exogenous shocks, such as Covid-19, regulatory or policy changes, energy price shocks, and climate developments that may have heterogeneous impacts within and across sectors.

The paper proceeds as follows. Sections 2 and 3 describe the data employed and the empirical evidence that motivates our approach. Section 4 presents the out-of-sample

[7] 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).

[8] 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.

forecasting exercise and the performance of the selected models. Section 5 discusses the impact of the carbon taxes on the default rates, while Section 6 concludes.

2 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 the Italian banks' default rates from the Italian Central Credit Register at the sector level.[9] This dataset comprises information at the borrower 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.[10] 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 and Michelangeli (2017)) and computed as the fraction of firms that are vulnerable within each sector.[11] 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 models (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: the default rates range from 0.2 percent in Q2 2006 to 23.3 percent 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 to 6.1 percent.

[9] 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.

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

[11] Vulnerable firms are those whose gross operating income is negative or whose ratio of net interest expense to gross operating income exceeds 50 percent.

3 Motivating evidence

As a first step, we analyse the raw pairwise correlations between the default rate and the share of vulnerable firms (debt) at the sector level and the in-sample explanatory power of the latter. Although there are differences in the magnitudes across sectors, a significant positive correlation links the default rates and the shares of vulnerable firms (and debt) for all the sectors (Table 1). 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 that include as regressors only the lagged share of vulnerable debt (or firms) capture well the dynamics of the default rate (Figure 1).[12] Furthermore, including the share of vulnerable debt helps improving the explanatory power on the sectoral default rates of alternative benchmark 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. (2021) can be informative to estimate the impact of alternative carbon taxes on the Italian banks' default rates.

4 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.[13]

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. We consider up to 3 lags of the regressors given the shortness of our sample. Among the macrovariables, we only focus on the real GDP growth rate since the in-sample analysis shows that adding other macroeconomic 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).[14] We use a recursive (expanding) windows

[12]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.

[13]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.

[14]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

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 dependent variable is $log(Def_t/(1-Def_t))$.[15] We also estimate all the models using a linear specification (i.e. where the dependent variable is the default rate); the results obtained with these two alternative specifications are very similar in terms of fit.[16]

Figure 2 illustrates the in-sample fit of the selected models for 1 quarter ahead. In the Appendix 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-sq. is about 0.46 versus 0.8) and is driven by the macroeconomic variables (i.e. the RGDP growth). This result is due to the fact that the default rates vary substantially around values very 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 and therefore can be omitted at this stage.[17]

quarters.

[15] 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 $E(e_t x) = E(x)$.

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

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

5 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 Faiella et al. (2021) 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. We estimate the effects on the default rates in the 2019 as the counterfactual data provided by Faiella et al. (2021) 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.

As discussed in Faiella et al. (2021), 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,[18] while €200-800 correspond to the value of the social cost of carbon in the event of a disorderly transition[19] as in the NGFS scenarios (NGFS (2021)). As explained in Faiella et al. (2021), 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 percent), €2.8 to each GJ of gas (+12 percent) and €0.12 to each litre of gasoline or gasoil (+8 percent). 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 3, 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 are statistically significant from the baseline rate only for the two most affected sectors (Agriculture and Services).[20] As observed in Faiella et al. (2021), 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

[18]Since June 2021 the price of emissions allowances has been firmly above €50, progressively increasing to €85 at the end of the year.

[19]The policies for the transition are postponed and when the process of reducing the emissions starts, it requires draconian measures as there are only a couple of decades left to achieve net zero.

[20]Note that we obtain large confidence intervals due to the shortness of our series.

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. (2021), these sectors are less reactive to changes in energy prices and hence suffer a larger increase in the energy expenditure.[21] The default rate for Agriculture increases from 2.3 to 3.2 percent with a €50 tax and to 6 with an €800 tax, while for Services it jumps from 1.9 to 3.1 percent with a €50 tax and to 5.1 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.[22]
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).[23] 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.[24]

6 Conclusions

Our work suggests a novel methodology to estimate the effect of alternative carbon taxes on the banks' credit risk. We find that the introduction of different carbon taxes within the range of €50-200 per ton, 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. The impact of an €800 carbon tax would be larger but still contained. The effect could still be more severe if the tax is applied during years with higher baseline default rates

[21] 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.

[22] This result is due to the fact that Faiella et al. (2021) 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.

[23] When we exclude the sectoral value-added, the impact for Agriculture is lower; with a €50 tax, the default rate increases to 2.9 percent, while with €800 to 3.7 percent.

[24] With the linear specification, the impact is slightly larger: with a €50 tax, the default rates would increase on average 1.48 times.

or different phases of the financial cycle.

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.

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7 Tables and figures

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

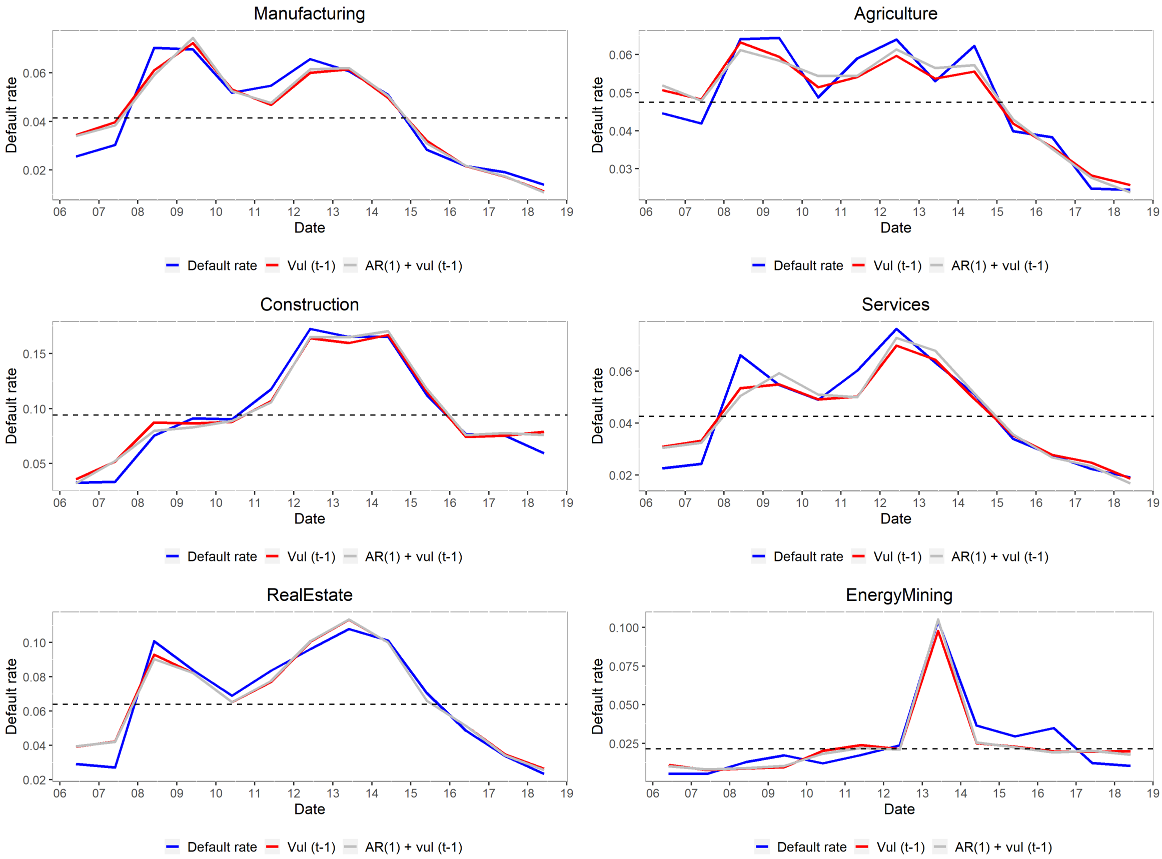
Note: Contemporaneous correlations at the sector level.

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

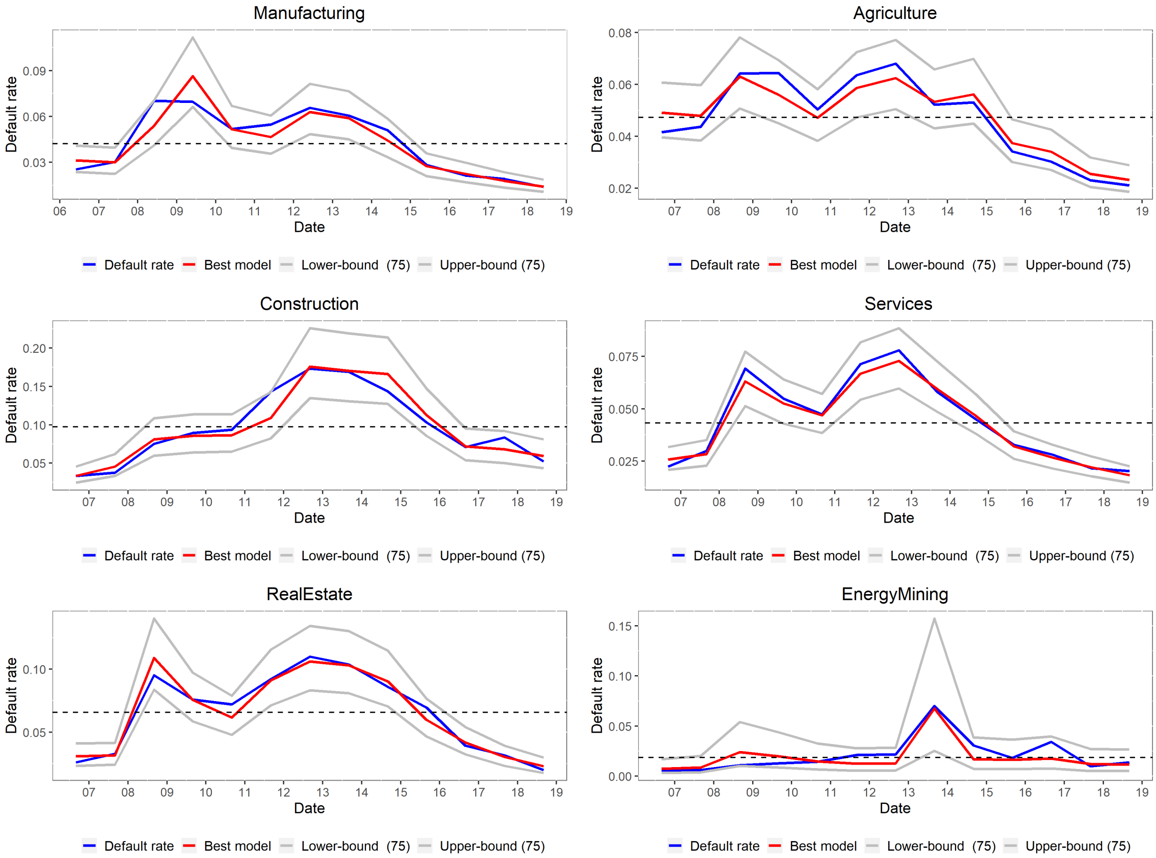
Note: Adjusted R-squared from the estimated models where the dependent variable is the default rate at time t. $Vuln.deb_{t-1}$ is the share of vulnerable debt for the same sector one quarter in advance. $RGDP\,gr_{t-1}$ is the RGDP growth rate a and Va_{t-1} is sectoral value-added one quarter in advance.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

Figure 1: 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 $Def.rates_t = \alpha + \beta * Vuln.deb_{t-1} + e_t$. 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. The data are smoothed with a 3 quarters moving average.

Figure 2: 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 he 75% confidence intervals. For Energy and Mining the specifications include a dummy for Q4 2013. The data are smoothed with a 3 quarters moving average.

Table 3: 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% 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.

Appendix

Table A4: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
				Manufacturing			
Share of vuln. firms	56	0.251	0.044	0.185	0.209	0.280	0.339
Share of vuln. debt	56	0.342	0.073	0.218	0.269	0.395	0.461
Default rate	56	0.041	0.022	0.013	0.023	0.060	0.098
				Agriculture			
Share of vuln. firms	56	0.455	0.040	0.388	0.415	0.499	0.520
Share of vuln. debt	56	0.508	0.102	0.327	0.412	0.590	0.684
Default rate	56	0.047	0.016	0.017	0.036	0.058	0.081
				Construction			
Share of vuln. firms	56	0.322	0.047	0.217	0.295	0.359	0.379
Share of vuln. debt	56	0.618	0.040	0.551	0.582	0.652	0.696
Default rate	56	0.094	0.049	0.028	0.048	0.131	0.190
				Services			
Share of vuln. firms	56	0.298	0.030	0.244	0.269	0.321	0.343
Share of vuln. debt	56	0.318	0.056	0.220	0.262	0.362	0.414
Default rate	56	0.043	0.021	0.017	0.024	0.055	0.099
				Real Estate			
Share of vuln. firms	56	0.298	0.030	0.244	0.269	0.321	0.343
Share of vuln. debt	56	0.318	0.056	0.220	0.262	0.362	0.414
Default rate	56	0.064	0.033	0.018	0.030	0.088	0.131
				Energy and Mining			
Share of vuln. firms	56	0.291	0.030	0.227	0.269	0.311	0.349
Share of vuln. debt	56	0.381	0.125	0.139	0.245	0.472	0.519
Default rate	56	0.021	0.032	0.002	0.007	0.023	0.233

Table A5: 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
	(0.143)	(0.136)	(0.137)	(0.112)	(0.144)	(0.131)
Def_rates$_{t-2}$	0.079	0.423***	0.203	0.419***	-0.188	
	(0.141)	(0.141)	(0.135)	(0.102)	(0.156)	
Def_rates$_{t-3}$	0.267**		0.368***		0.469***	
	(0.124)		(0.128)		(0.154)	
Vuln_debt$_{t-1}$			4.161***			
			(1.079)			
Vul$_{t-1}$	5.497***	17.557**		4.477***		
	(1.414)	(7.433)		(1.159)		
Vul$_{t-2}$		-16.069**				14.051
		(7.765)				(17.936)
Vul$_{t-3}$						-15.169
						(18.782)
Vuln_debt$_{t-3}$					1.803**	
					(0.705)	
RGDP gr$_{t-1}$					-19.383***	-21.688
					(6.191)	(12.987)
RGDP gr$_{t-1}$						-0.0001***
						(0.00001)
Va_$_{t-1}$		0.954		-23.483***		
		(1.296)		(5.819)		
Va_$_{t-2}$					1.878	
					(5.674)	
Va_$_{t-3}$	-1.798		0.245			-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