INTERNATIONAL MONETARY FUND

# Credit Risk Where It's Due: Carbon Pricing and Firm Defaults

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**WP/25/62**



**2025**
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WORKING PAPER

 

**IMF Working Paper**
Institute for Capacity Development

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Authorized for distribution by Selim Elekdag
March 2025



**ABSTRACT**: This study investigates carbon pricing-induced credit risk, the potential negative impact of carbon pricing on firms' ability to meet their financial obligations. Applying a well-established credit assessment model to a novel data set combining financial statements and emissions data, we subject the over 2.5 million borrowers of the euro area's largest banking groups to two carbon pricing stress scenarios. Our findings reveal a notable variation in impacts between and within sectors. However, even under the conservative scenario, many firms experience only a minimal increase in their probabilities of default. In the more realistic scenario, the aggregate impact on firms' creditworthiness is not material. The analysis further suggests that the capitalization of euro area banks would not be significantly affected by the carbon pricing-induced increase in corporate credit risk. While this study does not consider the macroeconomic transmission channels, it indicates that higher carbon prices are not likely to trigger widespread firm defaults and jeopardize financial stability.

**RECOMMENDED CITATION:** Löschenbrand, S., Maier, M., Millischer, L. and Resch, F. (2025). Credit Risk Where It's Due: Carbon Pricing and Firm Defaults *IMF Working Paper WP/25/62*.

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|---|---|
| JEL Classification Numbers: | G32, Q54, Q58 |
| Keywords: | Credit Risk, Climate Change, Transition Risk, Carbon Pricing |
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WORKING PAPERS

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# Contents

# 1 Introduction

By pledging to limit the global temperature increase to well below 2C above pre-industrial levels (UNFCCC, 2015), countries worldwide committed to fundamentally transform their economies towards carbon neutrality. This transition of the world economy away from greenhouse gas emissions comes with tight deadlines: to achieve the Paris Agreement's safer and more ambitious goal of limiting global warming to 1.5C, yearly greenhouse gas emissions have to peak before 2025 and decline by more than 40% before 2030 (UNFCCC, 2023).

Given the scale and speed of the necessary transformation, designing the right policies amounts to a difficult balancing act: delayed action exposes humanity to the fallout of an ever hotter climate (IPCC, 2022), while badly designed, drastic or unanticipated policies might unduly damage the economy and negatively affect livelihoods. In the business and finance literature, these two sources of risk have been labeled *physical risk* and *transition risk* respectively (IPCC, 2020).

Transition risk, which is the subject of this paper, is driven by the "societal changes arising from a transition to a low-carbon economy" (BCBS, 2021): public-sector policies, technological change, consumer preferences and investor sentiment. Among public sector policies aimed at reducing greenhouse gas emissions, *carbon pricing* plays a central role. It is widely considered the most effective climate change mitigation policy (Hepburn et al., 2020; Climate Leadership Council, 2019) and plays a crucial role in many countries' climate policy package (World Bank, 2023). Risks from poorly designed carbon pricing schemes are referred to as *carbon transition risks*.

The financial sector can play a critical role in the transition by financing the vast required investments (Internaional Engery Agency, 2021). But financial firms – and banks in particular – do not just *affect* the climate via their lending decisions, they are also *affected by* climate-related risks, in particular by carbon transition risk. Newly introduced or tightened carbon pricing schemes might increase traditional financial risks: credit risk, market risk and operational risk (BCBS 2021). The banking sector is aware of these risks and the role it can play in the transition to a less carbon-intensive economy, but the policy stance of the banking industry differs around the world (see, for example Europan Banking Federation (2022) and American Bankers Association (2022)).

*Carbon pricing-driven credit risk* arises when firms or households find it more difficult to meet their financial obligations due to the additional burden of a carbon price. This could come from a direct carbon tax they need to pay or indirectly, from a tax-induced increase in prices of purchased goods and services. Given that credit risk is the greatest risk on bank balance sheets (European Banking Authority, 2021) and that banks play a predominant role in many countries' financial systems (FSB, 2022), a badly designed carbon pricing scheme could, in theory, trigger an increase in credit losses and cause significant financial stability risks. It is therefore essential to quantify carbon pricing-induced credit risk to inform climate policy design.

In the literature, the relationship of firm credit risk and carbon emissions on the one hand (Carbone et al., 2021; Zhang and Zhao, 2022; Capasso et al., 2020; Safiullah et al., 2021) and carbon-related ESG scores on the other hand (Dumrose and Höck, 2023; Ramos-García et al., 2023) have been extensively studied. These analyses demonstrate that, even without any increase in carbon prices, markets and credit rating agencies consider firms with higher emissions less creditworthy, all else equal. Another strand of literature considers the impact of a "carbon pricing shock" on credit risk as one of the building blocks of central banks' climate stress tests (Vermeulen et al., 2018; Alogoskoufis et al., 2021; Guth et al., 2021; Mora et al., 2022; Jung et al., 2023; Emambakhsh et al., 2023; European Supervisory Authorities and European Central Bank, 2024). However, these analyzes consider a number of climate-related stress factors in their scenarios and do not explicitly report on banks' pure carbon pricing-induced credit risk. Finally, Faiella et al. (2022) and Aiello and Angelico (2023) estimate the financial impact of a carbon pricing shock on Italian firms and households and, subsequently, on banks, Nguyen et al. (2023) present a similar exercise for the United States and Schmittmann (2023) for Japan. Belloni et al. (2022) study the impact of rising carbon prices on banks by relying on a simple Merton-style model of firm asset dynamics and do not report firm- or sector-level impacts.

We are not aware of a systematic analysis focusing on carbon pricing-induced credit risk of both European firms *and* banks using a tried and tested credit risk model – and our study aims to fill that gap. Using a novel data set of financial statements and emission data in combination with the long-established credit assessment model developed by the Oesterreichische Nationalbank and the Deutsche Bundesbank (Leitner and Mayer, 2015), we apply a carbon pricing stress to firms' balance sheets and quantify the carbon pricing-induced credit risk of more than 750 European non-financial firms and subject the over 2.5 million non-financial firms with loans at the 81 largest European banks to the same two stress scenarios.

We show that, under the first, conservative, scenario, there is significant cross-sector variability in carbon pricing-induced credit risk, but a sizeable proportion of firms' probabilities of default remain practically unaffected. In the second – more realistic – scenario, the aggregate impact on firms' creditworthiness is virtually negligible and some of the cleaner firms actually *benefit* from a rise in carbon pricing. Accordingly, the short-term effect of the carbon pricing shock on the capitalization ratio of the biggest euro area banks, although non-negligible under the conservative scenario, does not lead to banks failing and does not pose a systemic threat to the stability of the banking system. This study does not account for the macroeconomic transmission channels of carbon pricing, as existing estimates in the literature vary widely and involve considerable uncertainty.

These results inform the design of carbon pricing and indicate that higher carbon prices, which would be warranted to achieve the goals of the Paris Agreement, seem to have only a limited impact on corporate credit risk and financial stability in Europe. While this study does not consider macroeconomic transmission channels and possible related feedback effects and non-linearities, it indicates that there is scope for more ambitious carbon pricing schemes that would speed up the transition and avert the fallout of unmitigated climate change.

The remainder of the paper is structured as follows. Section 2 outlines the employed methods and metrics. Section 3 describes the data sources and the sample. Section 4 presents the results. Finally, Section 5 discusses the findings and concludes.

# 2 Methods

Our approach consists of a firm and a bank module. In the firm module, we use OeNB's In-house Credit Assessment System (ICAS) model (Leitner and Mayer, 2015) to compute (un-)stressed probabilities of default (PD) in order to gauge the impact of a carbon pricing shock on the creditworthiness of firms. In the bank module, we analyze how firm-level impacts affect banks by looking at the change in the Common Equity Tier 1 (CET1) ratio.

This section first presents the two stress scenarios (Section 2.1), then gives details on the firm (Section 2.2) and the bank module (Section 2.3) and finally describes the metrics used for quantifying the impact (Section 2.4).

## 2.1 Scenarios

### Carbon price

We model a carbon pricing shock corresponding to an increase in the global price of carbon to EUR 100 per $tCO_2$ at the 2021 prices. This carbon price has been chosen as it is projected to be a suitable price to reach a 40% reduction of GHG emissions until 2030 and allows a smooth price increase to reach $CO_2$ prices consistent with the "Fit-for-55" plan proposed by the European Green Deal (Pietzcker et al., 2021). We consider a setting where the carbon price applies universally across firms' global emissions.[1] IMF simulations suggest that a uniform global carbon price of USD 50-80 per $tCO_2$ by 2030 could achieve the necessary emission reductions to align global greenhouse gas emissions with the 2C goal of the Paris Agreement (Parry et al., 2021; Chateau et al., 2022). However, according to Chateau et al. (2022), high-income countries would need carbon prices up to USD 225 per $tCO_2$ to achieve national reduction goals. As of 2021, the global carbon price was about EUR 3 per $tCO_2$ (Parry, 2021) and the effective price in the EU

[1] This could be achieved by either local pricing schemes or by carbon border adjustment mechanisms, where the carbon pricing is added as an import tariff (European Commission, 2021; International Monetary Fund, 2019).

was less than EUR 20 per $tCO_2$ (Parry et al., 2022).[2] Assuming a price of EUR 100 per $tCO_2$ can be considered a severe but plausible carbon pricing shock. In a sensitivity analysis, we consider a carbon price increase by EUR 200 per $tCO_2$ as price spikes might be even larger in adverse scenarios, e.g. in a delayed transition.

Taking the increase of the global carbon price to EUR 100 as an input, we will consider two scenarios: a raw and an enhanced stress scenario, which differ in the sophistication of their assumptions and are described in more detail in the following.

### Raw stress scenario

The raw stress scenario is designed to be simple and conservative. It does not rely on estimates of already paid carbon taxes (set to 0) or on models of the pass-through rate of carbon costs to consumers (also set to 0). These simple assumptions are relaxed in the "enhanced stress scenario" described further down.

In the raw stress scenario, firms need to pay EUR 100 per $tCO_2$ of global Scope 1 emissions[3]. Existing carbon costs (whether in the EU ETS, national carbon taxes, or other worldwide carbon pricing schemes) are not subtracted from that figure, meaning the raw stress scenario simulates an increase of the global carbon price *by* EUR 100 rather than *to* EUR 100. Scope 2 emissions costs are set to 0 as these are already accounted for as Scope 1 emissions in the electricity sector and no pass-through occurs.

While this scenario is designed to be simple and conservative in its treatment of firms, it has a number of shortcomings:

- First, the scenario does not consider that firms can offset some of their carbon costs by *raising costs for consumers and generating higher revenues*.

[2] The price of an EU ETS allowance was EUR 60 per $tCO_2$ in 2021 but the EU ETS only covers about half of EU emissions and half of the allowances were allocated for free. However, other carbon pricing schemes exist in the EU at the national level. Parry et al. (2022) computed an average price of about EUR 45 per $tCO_2$ as of 2022 (the prices in 2021 were lower) applying to less than half of emissions, hence the effective price of less than EUR 20 per $tCO_2$

[3] Scope 1 includes all direct greenhouse gas (GHG) emissions caused by a company itself. Scope 2 includes the indirect GHG emissions caused by a company's energy suppliers from generating electricity, heating, cooling and steam. Scope 3 includes all other indirect GHG emissions from the upstream and downstream value chain.

- Second, the raw stress scenario does not take into account that *firms face rising costs of intermediate goods and services* (which is consistent with the assumption of no pass-through).

- Finally, in this scenario, firms make *no changes to their production processes or business model* and implement no energy efficiency measures. Similarly, their balance sheet and income statement are assumed to remain unchanged beyond the increased carbon costs. This "business-as-usual assumption" is conservative, as firms' reaction to an increase in carbon prices would certainly aim at improving their financial position. This is why bank stress tests often make an analogous "static balance sheet assumption" (see e.g., Ong, 2014 and Alogoskoufis et al., 2021, Emambakhsh et al., 2023). As a robustness check, we investigate whether different balance sheet representations of the carbon costs impact the PD increase in Section 4.3.

### Enhanced stress scenario

The enhanced stress scenario is designed to address some shortcomings of the raw stress scenario, which comes at the expense of simplicity. In this scenario, we account for (a) the pass-through of carbon costs to consumers and (b) carbon costs firms already paid under the EU ETS. These features make the enhanced stress scenario more realistic and less conservative than the raw stress scenario, yet also more sensitive to a number of modeling assumptions.

**Carbon cost pass-through** In the raw stress scenario, firms face increased carbon costs, which weaken their balance sheets via reduced profits and are not offset by any positive cash-flow. In reality, firms would aim to raise their prices in order to pass on some of the carbon costs they face to consumers.

Since the introduction of the ETS in Europe, several studies have estimated cost pass-through for $CO_2$ pricing. These studies document significant and almost complete pass-through rates for the power sector (Sijm et al., 2006; Fabra and Reguant, 2014; Dagoumas and Polemis, 2020).

Evidence for a full carbon cost pass-through is also found for the petroleum sector (Alexeeva-Talebi, 2011; Cludius et al., 2020). Significant pass-through rates are also found for energy-intensive industries (cement, glass, iron and steel, chemicals), but these are associated with higher variation (from 20 to more than 100%, see Cludius et al., 2020). To the extent that energy price increases are informative approximations for carbon price increases, Ganapati et al. (2020) find significant pass-through rates between 27% (gasoline) and more than 100%-(cement, boxes, plywood) for different industries.

It should be noted that the EU ETS currently allows for exemptions from carbon pricing via a system of free allocations, primarily for energy-intensive industries. It is often argued that these industries are unable to pass on costs to customers because of international competition. Hence, to prevent "carbon leakage", i.e., the shifting of greenhouse gas emissions from the EU to countries with lower carbon costs, they receive free allowances. The introduction of the Carbon Border Adjustment Mechanism (CBAM)[4] aims to prevent carbon leakage. CBAM thus helps to reduce emissions from the production of imported goods and should allow more cost pass-through for producers within the EU.

In general, cost pass-through is difficult to model, as it requires detailed information on a firm's cost structure and competition. Think of a retailer: accounting for cost pass-through ultimately leads to a change in costs and product prices at every step in the value chain, from purchased goods to transport and storage. Thus, a realistic model would need to consider upstream and downstream Scope 3 emissions as well, to incorporate the indirect effect due to the price increase of input factors (raw materials and intermediate goods) and the shift in customer demand driven by additional carbon costs when using the product.

For the purpose of the enhanced stress scenario, we use the following pass-through assumptions. Firms in the energy sector[5] are modeled like electricity companies. The most carbon-intensive firm is assumed to be the marginal producer and can pass on 90% of its additional

[4]CBAM sets a level playing field for domestic European production and foreign production by adding the embedded emissions as a tariff for imported goods and will enter into force in 2026 with reporting already compulsory (see European Commission (2021)).

[5]Firms operating in NACE classes 35.00, 35.10, 35.11, 35.12 35.13, 35.14 and 35.30.

carbon costs, i.e., their revenue increases by 90% of additional carbon costs. All other firms benefit from raising prices, i.e., they receive the same proportional increase in revenue as the marginal producer. For companies in all other sectors, these additional costs are added to the stress as Scope 2 emissions. Furthermore, we simply assume that they are able to pass on 50% of their total carbon costs to customers, i.e., their revenue increases by 50% of said additional carbon costs. We discuss this simple assumption in Section 4.3.

**Paid EU ETS carbon costs** As explained in Section 2.1, we want to simulate the increase of the global carbon price *to* EUR 100 and therefore have to take into account that firms already pay a price on parts of their emissions. Following Millischer et al. (2023), we compile the emissions and free allowances of firms under the EU ETS, which is the largest and most expensive pricing scheme.

The carbon costs that firms have paid under the EU ETS are estimated as the emissions covered minus the free allowances received multiplied by the observed average price of EUR 60 per $tCO_2$. By considering the already paid carbon costs, we are much closer to the impact of an increase of carbon prices *to* EUR 100 rather than an increase *by* EUR 100 as in the raw stress scenario. It should be noted, however, that the globally operating groups in our sample are subject to a number of carbon pricing schemes other than the EU ETS (see World Bank, 2023 for a comprehensive list of schemes) and, due to the lack of available firm-level data, we do not consider the costs they incur under those smaller schemes.

### Macroeconomic transmission

Importantly, the two scenarios described above do not include the macroeconomic impact related to an increase of the global carbon price as those would add an additional source of uncertainty to the estimates. Indeed, estimates of the aggregate impact of carbon pricing on output and employment vary significantly. Some studies find a negative impact (Känzig, 2023, Tao et al., 2024, International Monetary Fund, 2022b), others find impacts can be both positive or negative depending on revenue recycling and modeling choices (Anger et al., 2010, Kober et al., 2016, Kettner et al., 2024, Schoder, 2021), while most conclude the results are likely to be small (European Central Bank, 2023b, International Monetary Fund, 2022a, Lee et al., 2024, Martin et al., 2014, Metcalf and Stock, 2023, Venmans et al., 2020, Abdullah and Morley, 2014, Boonman et al., 2024, Pollitt et al., 2022).

Over the medium-term, those studies that investigate the sectoral impacts of carbon pricing find – in line with the stated policy goal – that the highest-emitting sectors tend to shrink in favor of lower-emitting sectors. It is not unlikely to assume that over the medium-term the creditworthiness of firms in the most affected sectors might decrease. However, a study of the medium-term effects on the creditworthiness is different in nature to the analysis we present here: it requires a relaxation of the static balance sheet assumption in favor of assumption-driven dynamic modeling.

In summary, our work should be seen as a robust and transparent *short-term sensitivity analysis* of carbon pricing, setting the macroeconomic transmission channel aside.

## 2.2 Firm module

In the firm module, we use OeNB's credit risk model to quantify the impact of our two carbon stress scenarios on the firms' creditworthiness.

**Credit risk model** At the core of this study's analysis lies OeNB's credit risk model. The model is operated as part of OeNB's in-house credit assessment system (ICAS) for the purpose of accepting bank loans as collateral for monetary operations in the euro area.[6] The model is based on consolidated financial statements, credit register data and default information from the entire universe of Austrian, Germany and Greek IFRS companies. The model is calibrated on the ICAS default definition which builds upon the Basel III default definition, i.e., it considers unlikeliness to pay and 90-days past due as default events.[7] It features six financial ratios which

[6]See Auria et al. (2021) for an overview over in-house credit assessments in the euro area.
[7]For more details on the calibration methodology see Leitner and Mayer (2015).

are weighted to obtain a credit score.[8] This score is transformed to obtain an issuer-specific, point-in-time, probability of default estimate for a one-year horizon. Thus, the model can be employed to assess changes in the probability of default without reverting to modeling default events, an approach often used in other stress testing exercises.

In the past, the model has been successfully applied to also rate Belgian, Spanish and Portuguese firms, using their IFRS financial statements, see Leitner and Mayer (2015). Since its first introduction in 2011, the model has consistently shown excellent performance regarding discriminatory power and calibration quality in the Eurosystem's annual performance monitoring.[9]

**Carbon stress** In our carbon stress model, we simulate the impact of a hypothetical $CO_2$ price increase on the creditworthiness of firms by following four steps. First, we determine the Scope 1 and Scope 2 emissions for each company. Second, we compute additional costs stemming from a higher $CO_2$ price. For the raw stress scenario, these costs come on top of already existing expenses. In the enhanced stress scenario, we recognize already paid expenses under the EU ETS (increase *to* 100 EUR), add the costs passed on from Scope 2 emissions and allow firms to pass on carbon costs to consumers. Third, we run the financial projection in line with EU ETS and IFRS accounting rules.[10] We assume that carbon costs are paid via the "cash and deposits" balance sheet item. If these accounts are insufficient, companies borrow, i.e., they increase their indebtedness. Fourth, we use stressed positions as the basis for stressed credit risk rating assuming an otherwise static balance sheet, i.e., no additional investments are undertaken, and profits and losses are affected only by the additional costs for $CO_2$ emissions.

[8]Five of those financial ratios are stressed when modeling an increase carbon price (EBIT, self-financing ability, net indebtedness ratio, return on cash flow, EBITDA - ROI) and one is not (capital interest burden). The capital interest burden is defined as total interest payments divided by total debt. By not stressing this model variable, we assume that the average interest rate of a firm is not impacted by the carbon price shock.

[9]The Eurosystem accepts collateral assessed by various rating sources as part of the Eurosystem Credit Assessment Framework. For more details, see European Central Bank (2023a).

[10]Therefore, we assume that the emission cost is incurred via the obligation to purchase permits for every $tCO_2$ emitted during the production process in the respective fiscal year (t). The allowances for the expected emissions are bought and paid via cash and deposits within the same period (t). Certificates are kept in stock and submitted in the year after (t+1).

## 2.3 Bank module

In the bank module, we translate the firm-level PD impacts into a bank-specific capitalization-ratio changes by "stressing" banks' credit exposure to non-financial firms.[11] The effect is computed for the 776 firms for which firm-level data are available and separately for all other firms for which a loan exposure is recorded in Anacredit, the Eurosystem's credit register (European Central Bank, 2016). For the latter, stressed PDs are obtained by extrapolating the link between emission intensity and PDs observed in the firm module (see A.3.5).[12] Country-sector average emission intensities are used as input whenever firm-level data are not available (for details, see Section 3). To account for the heterogeneity of emissions within a sector, we carry out a Monte-Carlo simulation.[13] We combine the dispersion of emission intensities observed in the firm-level data set with the Eurostat country-sector averages and input these into our extrapolation model to derive distributions for the bank-level metrics outlined in Section 2.4. In general, we present the averages of these distributions in the results.

For our analyses, we assume that banks follow the internal rating-based (IRB) approach and the International Financial Reporting Standards (IFRS) to determine capital requirements and expected loss provisions. The starting point is the unstressed Common Equity Tier 1 ratio defined as

$$CET1r = \frac{CET1}{RWA}. \tag{1}$$

where $CET1$ is the common equity tier 1 capital and $RWA$ are the risk-weighted assets. Using stressed PDs and the stressed loss given default (LGD) as an input, we obtain additional provisions and increased risk-weighted assets for each firm, resulting in a stressed CET1 ratio at bank level,

$$CET1r^{*} = \frac{CET1 - \sum_{f \in firms} \Delta \text{provisions}_f}{RWA + \sum_{f \in firms} \Delta RWA_f}. \tag{2}$$

[11] Household, government and financial-sector credit exposure as well as market risk exposure are left unstressed.

[12] We show that other firm-specific variables apart from the emission intensity have no significant impact on the PD shock in Section A.3.5.

[13] Further details are given in A.3.4

Firms' loss given default (LGD) is expected to increase in line with the PD according to the approach by Frye and Jacobs (2012). The increase of a firm's PD and LGD leads to higher expected losses on the one hand (for which banks need to build additional credit risk provisions, according to IFRS9, including lifetime provisions for exposures with significantly increased credit risk), and on the other hand to increased risk weights (which are computed according to the Basel IRB formula) and therefore higher risk-weighted assets (RWA). The two effects, respectively, decrease the numerator (available capital) and increase the denominator (RWA) of the capitalization ratio and therefore lead to lower CET1r. The detailed methodology is described in A.3.

## 2.4 Metrics

The stress caused by the carbon pricing shock, both at the firm and at the bank level, will be measured by several metrics, which are presented below.

### Firm-level metrics

The *stressed PD factor* ($F^*_{PD}$) is defined as the ratio of the stressed ($PD^*$) to the unstressed ($PD$) prediction of the probability of default and measures the relative increase,

$$F^*_{PD} = \frac{PD^*}{PD}. \tag{3}$$

Credit rating scales typically show an exponential link between rating grades and probabilities of default. The stressed PD factor can therefore be interpreted similarly to a rating migration but without the discretization effect induced by using rating grades [14]. *Rating migrations* are measured on a rating scale equivalent to the Standard & Poor's (S&P) rating scale including the classification as investment grade.

The *stressed PD difference* ($\Delta PD^*$) is defined as the difference between the stressed and the

[14] A one notch downgrade approximately corresponds with a PD factor of 1.5

unstressed PD predictions and is measured on an absolute scale,

$$\Delta PD^{*} = PD^{*} - PD. \tag{4}$$

Once multiplied with the exposure, the stressed PD difference is a measure of the change in the expected loss incurred by the stress scenario.

**Bank-level metric**

In order to gauge the relevance for financial stability of the deterioration of firms' creditworthiness, we look at the impact on the common equity tier 1 ratio ($CET1r$) defined as the difference between the $CET1$ ratio after ($CET1r^{*}$) and before the stress ($CET1r$),

$$\Delta CET1r^{*} = CET1r^{*} - CET1r. \tag{5}$$

If not indicated otherwise, we present the bank-level averages of the Monte-Carlo simulation.

## 2.5 Summary of methodology and metrics

Figure 1 illustrates the steps of our carbon stress model for firms and banks in the raw scenario. Note that the enhanced scenario deviates only with respect to the cost increase in the firm module, where there may be a net benefit from increased revenue for some firms rather than a cost increase.

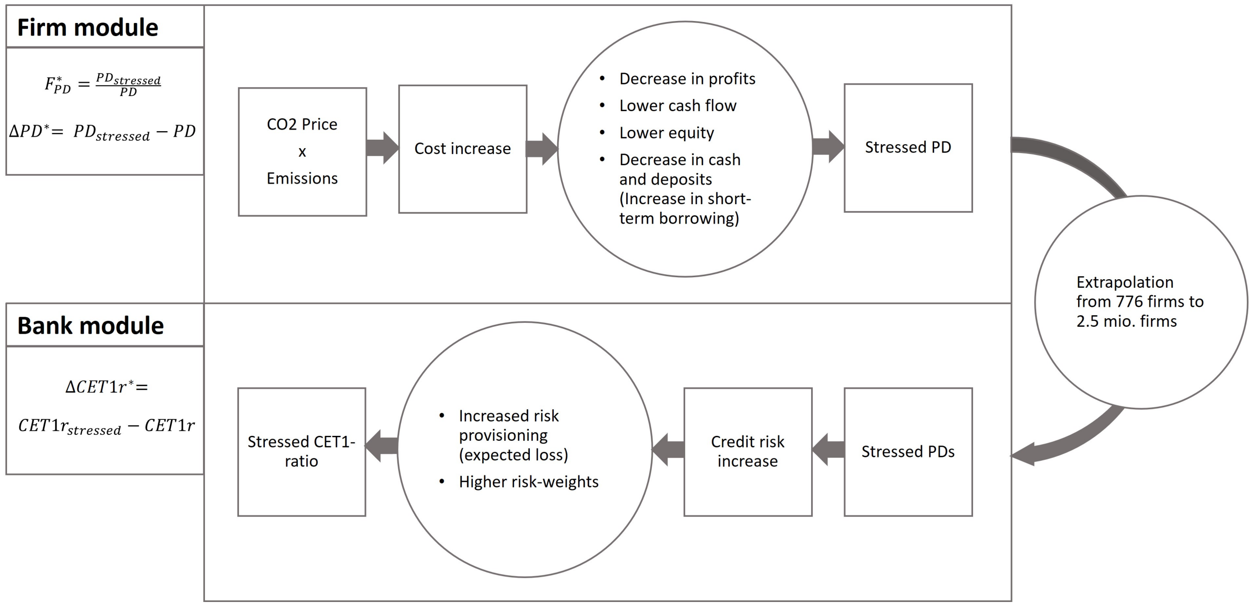


**Figure 1:** Sketch of the stress model in the raw scenario.

# 3 Data

In our research, we use the most granular data sources available for firm-level and bank-level data. If no granular information is obtainable, we revert to country-sectoral data and account for the heterogeneity via the simulation exercise.

## 3.1 Firm-level data

We consider a firm at firm-level, if a consolidated financial statement and carbon emissions are available at the firm-level. We complement this information with data from the EU Emission Trading System (EU ETS).

**Financial statement data** Financial statement data are taken from the European Records of IFRS Consolidated Accounts (2023) database[15] which provides financial statements from listed,

[15] Micro data are currently only available to participating institutions while access to aggregated data is described in European Records of IFRS Consolidated Accounts (2023).

non-financial firms following the IFRS[16] in a harmonized format. For the fiscal year 2021, we obtain consolidated financial statements for 881 groups listed in one of the participating countries (Austria, Belgium, France, Italy, Germany, Greece, Portugal, and Spain).

**Global emission data** Emission data are retrieved from the ERICA database and from third-party data providers (ISS ESG and Carbon 4 Finance). The ERICA database holds information on the global $CO_2$ emissions taken from the groups' IFRS reports or from separate sustainability reports. As of 2021, the publication of emission data remains a voluntary reporting under the European legal framework (European Parliament and Council, 2014). Hence, emission data are not available for all groups and, when available, are not based on a harmonized methodology. For the analysis, we do not distinguish between groups reporting only $CO_2$ emissions and groups reporting all greenhouse gases in $CO_2$ equivalents.

In addition, we use two additional data sources (ISS ESG and Carbon 4 Finance) providing a large set of variables related to companies' climate risk, including Scope 1 and Scope 2 emissions. Regarding data from ISS ESG and Carbon 4 Finance, we consider modeled and reported information.[17]

When available, reported information is preferred to modeled data. If emission data are available from two or more sources for an entity, we use the source closest to the peer-group[18] median. As a data quality validation, we also check whether Scope 1 emissions are lower than those reported under the European Union Emissions Trading System (EU ETS) as European emissions are a subset of global Scope 1 emissions.

In our study, we consider direct (Scope 1) and indirect (Scope 2) emissions, but treat them differently in the two scenarios (see Section 2.1). Scope 3 emissions, however, are reported less frequently and are often assumption-based. Hence, at the time of the study, they were not seen

[16] International Financial Reporting Standards (IFRS): Accounting standard that must be followed by publicly traded parent companies in the EU when preparing consolidated financial statements and is issued by the International Accounting Standards Board (IASB).

[17] The data providers estimate emissions for companies where information is not available based on other variables. Also, they run internal validations of the emission information reported by companies.

[18] We define 19 peer-groups based on NACE codes and look for the median emission intensity in $tCO_2$ per euro of revenues.

as sufficiently comparable and suitable.

For the main share of the banks' portfolio, no firm-level emission data are available. For these entities, we revert to the Scope 1 emission intensities at country-sector level (NACE level 1 and for high-emitting subsectors level 2) from Eurostat (2024) and generate distributions of the emission intensity for each firm in the simulation exercise. To obtain the scope 2 emissions we scale the Scope 1 emissions using the factors observed at firm-level and the Eurostat sector data from the electricity sector.

**EU ETS emissions and costs** The European Union Emissions Trading System (EU ETS) is the world's largest carbon pricing scheme,[19] and covers electricity and heat generation, energy-intensive industries, and the aviation sector. Every year, installations in these sectors need to surrender allowances for the greenhouse gases they emit. A fraction of these allowances is allocated to the installations for free,[20] while the residual needs to be covered with allowances purchased in public auctions or on the secondary market.

In order to gauge (a) what fraction of the emissions of the firms in our sample were covered by the EU ETS and (b) how much firms needed to pay for these emissions, we follow the standard aggregation methodology of Millischer et al. (2023). Installations in the EU ETS database, for which yearly emissions and free allowance allocations are known, are matched with the ORBIS firm database. Using the ORBIS ownership structure, we determine whether a firm in the ERICA sample owns a controlling share in that installation, then sum over all controlled installations to obtain a firm's emissions and free allowance allocation. For the firms without financial statements we use the share of paid EU ETS emission on sector-level as a proxy in the enhanced stress scenario.

[19] 1.36 billion tons of $CO_2$ ($tCO_2$) equivalent were covered by the EU ETS in 2021, see European Environmental Agency (2023)

[20] This fraction varies from sector to sector and typically increases with the risk of "carbon leakage", that is firms moving emissive production to other jurisdictions in order to circumvent carbon pricing policies. Since 2013 the fraction has been very low for the electricity sector.

## 3.2 Bank-level data

In addition to the firm-level data, we require bank-level data for the capitalization ratios and the banks' portfolio composition.

**Bank capitalization ratios** The European Banking Authority (2021) (EBA) annually publishes bank-level data from the mandatory reporting covering the banks' consolidated financial statement (FINREP) and capital requirements (COREP) in its transparency exercise. Data from the largest 112 European banks are available at the highest level of consolidation from which we use the values on the Common Equity Tier 1 capital (CET1), total and corporate Risk-Weighted Assets (RWA) and the portfolio composition on sectoral level in the financial statement.

**Bank portfolios** Granular information on the banks' portfolio composition is available from the Euroystem-wide credit register called AnaCredit (European Central Bank, 2016). The data set contains information at borrower-lender-level on the exposure and, for banks following the IRB approach, PDs. Missing PDs are imputed using country-sector averages. To account for the exposures not reported in AnaCredit (e.g., the lending via subsidiaries outside the Eurosystem), we scale up exposure values from AnaCredit to match the exposures reported at the consolidated level in European Banking Authority (2021). Furthermore, we restrict the portfolio to banks where at least 5% of the RWA stem from corporate RWA and where data in AnaCredit are available. This results in a sample of 81 banks.

## 3.3 Stylized facts

Below we present some stylized facts summarizing the numerous data sets used in the analysis. Additional break-downs are given in A.1 and A.2.

### Firm-level data

In this section, we describe the baseline situation before applying the carbon pricing shock: firms' initial creditworthiness and emission intensity. The sample comprises financial statement and emission intensity data for 776 firms for the fiscal year 2021. An overview is presented in Table 1.

| Firm size | Corp. publication | Modeled | Total |
|---|---|---|---|
| Small | 47 | 205 | 252 |
| Medium | 169 | 79 | 248 |
| Large | 257 | 19 | 276 |
| Total | 473 | 303 | 776 |

**Table 1:** Emission data by source and firm size: Small if revenue $<$ EUR 250 Mio., Medium if EUR 250 Mio. $\leq$ revenue $<$ EUR 1,500 Mio., Large if revenue $>$ EUR 1,500 Mio.

The sample is further structured in climate policy relevant sectors (CPRS) and non-CPRS (Battiston et al., 2017) with 469 firms belonging to CPRS and 307 firms classified as non-CPRS.[21]

**Creditworthiness** Figure 2 shows the baseline predictions (pre-carbon pricing shock) of our rating model (see Section 2.2) measured on the rating scale by Standard & Poor's (S&P) [22] with 469 of 776 entities reaching investment grade. The share of investment grade companies is higher in the fossil-fuel, utility and energy-intensive industries sector.

**Emission intensity** Figure 3 presents the distribution of Scope 1 and Scope 1+2 emission intensities – firms' emissions normalized by revenue. Scope 1 and Scope 1+2 (total) emission intensities are generally well aligned (Kendall's tau $= 0.75$). The fossil fuels and utilities sector are associated with pollution levels multiple times higher than other sectors on average. We record a median total intensity of 231 and 434 $tCO_2$/Mio EUR of revenue for fossil fuels and utilities respectively. Further, our sample of the third sector of energy-intensive manufacturing is charac-

[21] Given the low number of reporting entities in sector scientific R&D, we collapse sectors scientific R&D and other into "Non-CPRS" for the remainder of the analysis.

[22] The output of the rating model is a one-year probability of default, which is associated with the S&P rating scale based on the historical default rates observed by S&P.

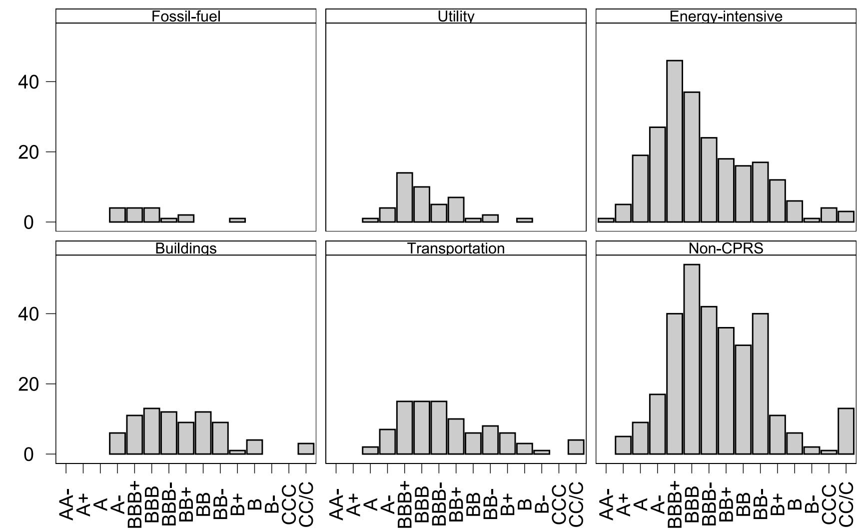


**Figure 2:** Distribution of base ratings on the S&P scale

terized by relatively low emission intensities, reporting a median value of 34 $tCO_2$/Mio EUR of revenue. However, there are several observations with significantly higher intensities, suggesting that the energy-intensive sector is very heterogeneous. The transportation sector shows a slightly higher median intensity of 39 $tCO_2$/Mio EUR. Buildings report a median intensity of 25 $tCO_2$/Mio EUR. Non-CPRS businesses record a median intensity of 17 $tCO_2$/Mio EUR, also showing some heterogeneity.

Table 2 presents the relationship between global direct (Scope 1) emissions and emissions covered through the EU ETS (in the third column) and the share of global emissions for which free allowances are handed out under the EU ETS (forth column). In total, we record 770 $MtCO_2$ emitted through direct emissions globally in 2021 and 373 $MtCO_2$ (48%) covered through the EU ETS. Roughly one third of the companies' global emissions are already priced under the EU ETS.

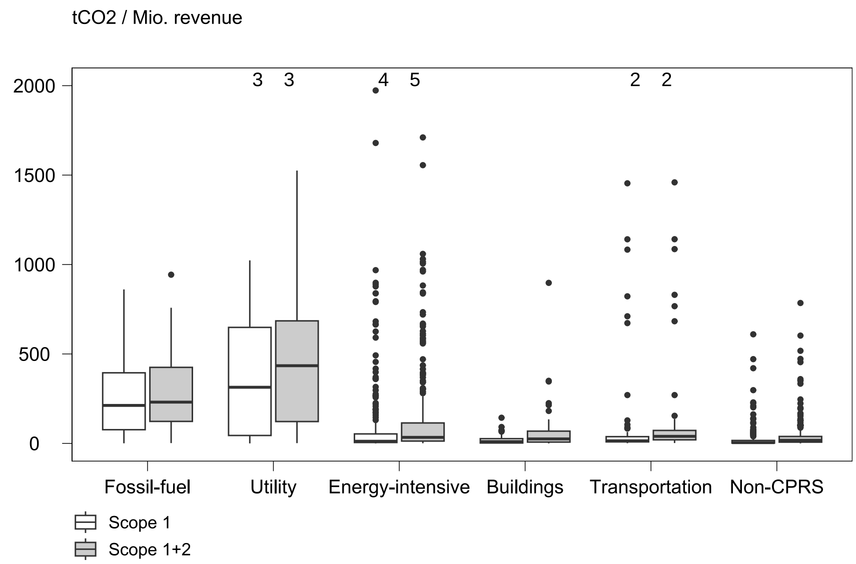


**Figure 3:** Emission intensity by sector. The boxes show the $25^{th}$, $50^{th}$, and $75^{th}$ percentiles of the distribution, and the whiskers correspond either to the min or max, or to 1.5× interquartile range. The number of observations above the cut-off is indicated at the top.

| CPRS sector | Scope 1 emissions | EU ETS share | Free share |
|---|---|---|---|
| Fossil-fuel | 86 | 67% | 40% |
| Utility | 346 | 60% | 2% |
| Energy-intensive | 246 | 37% | 30% |
| Buildings | 5 | 5% | 3% |
| Transportation | 70 | 20% | 12% |
| Non-CPRS | 16 | 10% | 7% |
| Total | 770 | 48% | 16% |

**Table 2:** Global direct (Scope 1) emissions [in $mtCO_2$] of firms in our sample by sector and share covered through the EU ETS. The last column presents the share of global emissions that are covered by free EU ETS allowances.

### Bank-level data

The 81 banks in our sample report a total of EUR 7,016 bn in total risk-weighted assets. As presented in Figure 4,[23] the CET1r of these institutions varies between 8.4% and 38% and is 14.9% at the system level. Corporate credit risk exposure accounts for 43.7% of total risk-

[23] Table 9 in the Appendix shows detailed statistics.

weighted assets on average. The share of exposure of the 776 IFRS groups firms in the firm-level data set is on average 7%.

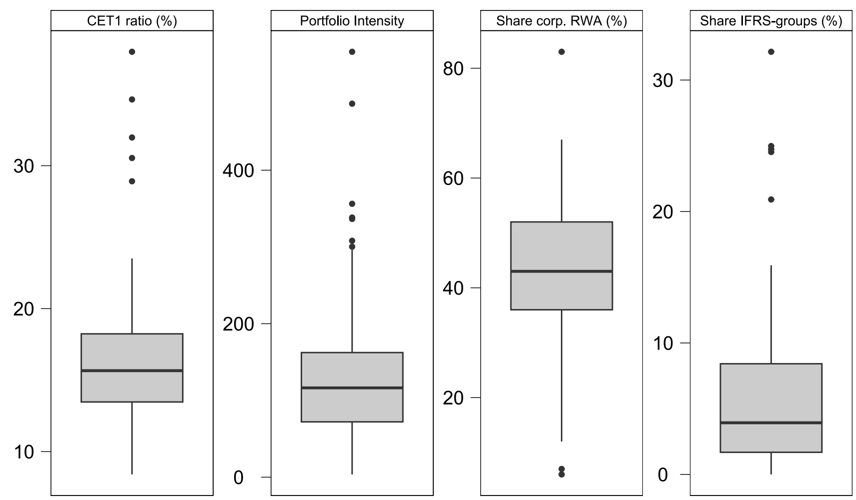


**Figure 4:** Pre-stress distributions of main bank-level variables for the sample of 81 significant institutions. The first column shows the distribution of banks' the initial capital ratio. Column two reports the exposure weighted $CO_2$ intensity for the banks' portfolio in $tCO_2e$ per million euro revenue. Column three indicates the share of a banks total risk-weighted exposure that is affected by our stress (the share attributable to corporate credit risk). The last column reports the share of the exposure attributable to our sample of 776 IFRS-groups.

## 3.4 Summary of data sources and calculated values

Table 3 summarizes the data sources and the calculations underlying our calculations. A detailed summary of the methodology is given in A.3. Note that the firm-level data set consists of 776 firms while the *Other firms data set* comprises over 3.3 million borrower-lender relationships for more than 2.5 million firms.

| | Firm-level data set | Other firms data set |
|---|---|---|
| $RWA_i$ | European Banking Authority | |
| $CET1_i$ | European Banking Authority | |
| Financial statements $FS_f$ | ERICA | - |
| Emission intensity $EI_f$ | ERICA, ISS, C4F | MC sim. based on Eurostat |
| Paid emissions $PE_f$ | EU ETS | Extrapolation($PD_f$, $EI_{sim,f}$) |
| $PD_f$ | ICAS model($FS_f$) | Anacredit |
| Exposure $EXP_{i,f}$ | Anacredit | |
| $LGD_i$ | Implied($RWA_i$, $EXP_{i,f}$, $PD_{i,f}$) | |
| $RW_{i,f}$ | Basel formula($PD_f$, $LGD_i$) | |
| $PD^*_f$ | ICAS stress model($FS_f$,$EI_f$,$PE_f$) | Extrapolation |
| $LGD^*_{i,f}$ | Frye-Jacobs($LGD_i$, $PD_f$, $PD^*_f$) | |
| $RW^*_{i,f}$ | Basel formula($PD^*_f$ , $LGD^*_i$ ) | |
| $\Delta$ provision$_{i,f}$ | IFRS staging($PD_f$, $PD^*_f$, $EXP_{i,f}$) | |
| $\Delta$ $RWA_{i,f}$ | $EXP_{i,f} \times (RW^*_{i,f}$ - $RW_{i,f})$ | |
| $CET1r^*_i$ | See Equation 2 | |

**Table 3:** Summary table of data sources and calculated values with the subscripts $i$ for banks and $f$ for firm

# 4 Results

This section presents the results of a carbon price shock as defined in the raw and the enhanced stress scenario, first in terms of increased firm PDs (Section 4.1) and then in terms of capitalization ratios of European banks (Section 4.2). For bank-level results the mean of risk metics from the Monte-Carlo simluations is presented, while the dispersion is analyzed along with further checks as part of the sensitivity analysis (Section 4.3).

## 4.1 Impact on firm probabilities of default

### Raw stress scenario

Figure 5 presents boxplots of the stressed PD factor, i.e., the ratio of stressed to baseline PDs for the 776 firms, split by sectors. Panel A confirms that the sectors fossil fuel and utility are most affected under the raw stress scenario, with median PD increases of 18% and 19% respectively and third-quartile increases of 66% for the fossil-fuel industry and 113% for utilities. All other sectors show no widespread shift, but a significant impact on individual companies.

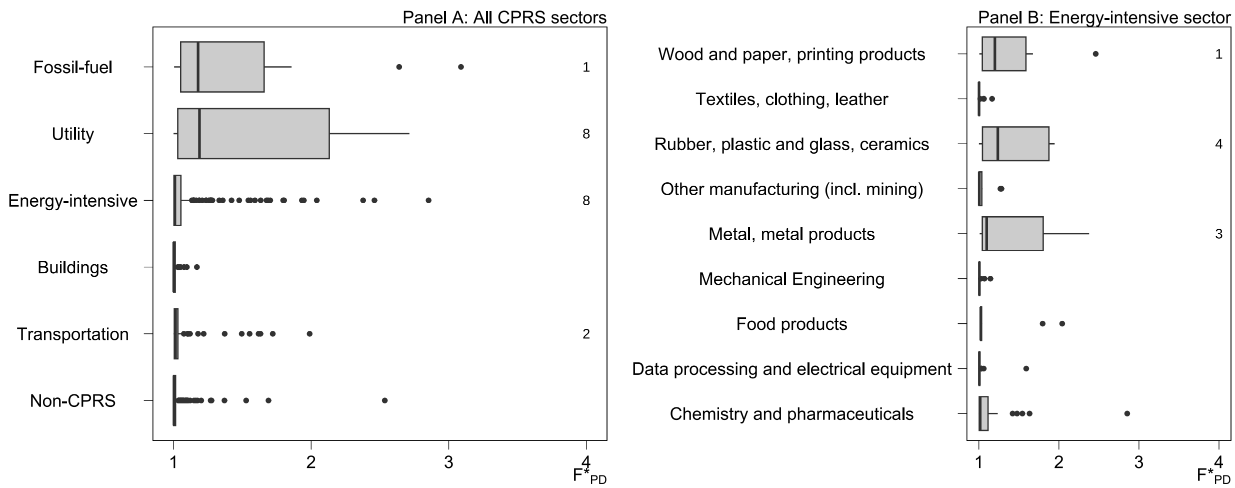


**Figure 5:** Impact, in terms of stressed PD factor $F^*_{PD}$, of the carbon shock in the raw stress scenario on firm creditworthiness, by sector. The boxes show the $25^{th}$, $50^{th}$, and $75^{th}$ percentiles of the distribution, and the whiskers correspond either to the min or max, or to 1.5× interquartile range. The number of observations above the cut-off is indicated at the edge. See table 5 in the Appendix for a summary table. Note: the four outliers in the "Rubber, plastic and glass products, ceramics" category on Panel B are cement companies.

A more granular subsector classification highlights the heterogeneity within the energy-intensive sector (Figure 5, Panel B).[24] The sectors "metallic manufacturing and metal production", "wood and paper industry" as well as "rubber, plastic and glass production, ceramics" record a strong increase due to the stress, comparable to the fossil fuel and utility sector. On aggregate, the debt-weighted sample PD[25] increases from 0.41% to 0.60%. A summary table is provided in the Appendix (Table 5).

Measured on an absolute scale as shown in Figure 6, PD increases are rather small: below 1 percentage point (pp) increase for almost all firms and below 0.1 pp for most firms in all but the utility sector. Only in the "metal production and manufacturing of metal products" subsector shows a more widespread shift for the upper half of the 17 firms. It should be noted, however,

[24] 236 firms in our sample belong to the energy-intensive sector.

[25] PD weighted by outstanding firm debt as reported in the financial statement.

that baseline PDs in that sector are among the highest (see Figure 2, which shows the rating grade distribution before the stress). A summary table is provided in the Appendix (Table 6).

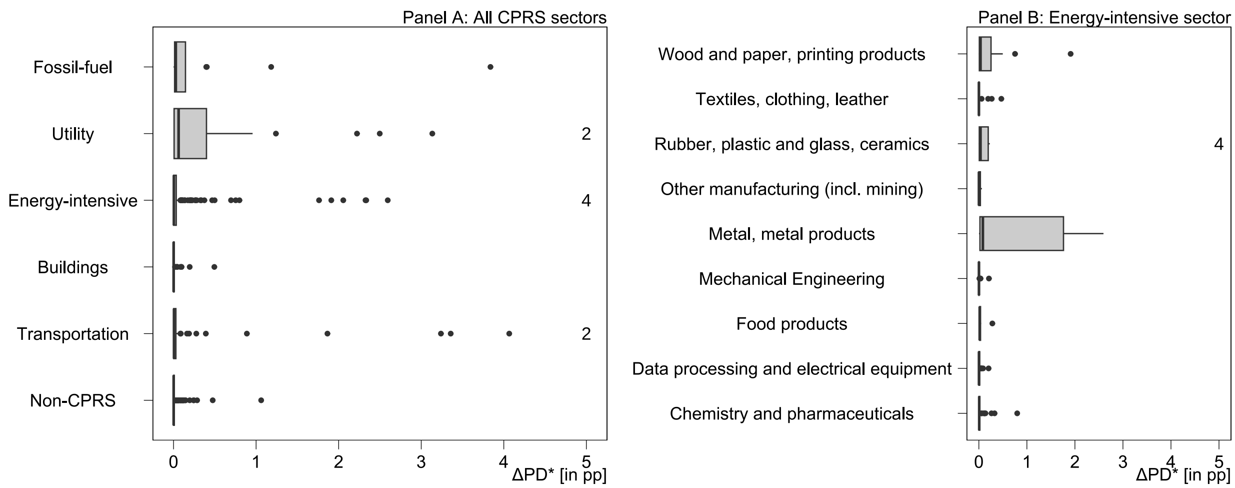


**Figure 6:** Impact, in terms of stressed PD difference $\Delta PD^*$, of the carbon shock in the raw stress scenario on firm creditworthiness, by sector. The boxes show the $25^{th}$, $50^{th}$, and $75^{th}$ percentiles of the distribution, and the whiskers correspond either to the min or max, or to $1.5\times$ interquartile range. The number of observations above the cut-off is indicated at the top. See table 6 in the Appendix for a summary table.

The increase in PDs described above also translates into mild rating migrations.[26] Under the raw stress scenario, 88% of firms would *not* be downgraded.[27] Downgrades typically affect firms with high absolute emissions: firms downgraded from investment grade to non-investment grade produce 43% of total emissions.

These are the results for the rather conservative raw stress scenario. Next, we present the impact on PDs under the enhanced stress scenario, in which we account for already incurred carbon costs and allow for (partial) cost pass-through.

[26] Table 7 in the appendix shows the detailed statistics.

[27] In the utility sector, where emission intensities are highest, more than half of the 45 firms would be downgraded by at least one notch. Likewise, in the fossil fuel sector, 8 of 16 companies would be associated with a downgrade and 17% of companies in the energy-intensive industries. The stress simulation indicates a drop in credit quality below investment grade for only 6% of the sample companies (from an initial 60% with investment grade), again particularly among utilities but also for energy-intensive manufacturers and fossil-fuel industries. Measured in terms of debt, this translates into 4% of total volume migrating to a non-investment grade.

### Enhanced stress scenario

Figure 7 presents the impact on firm PDs under the enhanced stress scenario: accounting for existing carbon costs and increased revenue because of cost pass-through reduces stress significantly: 91% of firms see their rating unchanged or upgraded.[28] In the enhanced stress scenario, the aggregate debt-weighted PD increases from 0.41% to 0.48%, which marks a 12 bp lower stressed PD compared to the raw stress scenario.

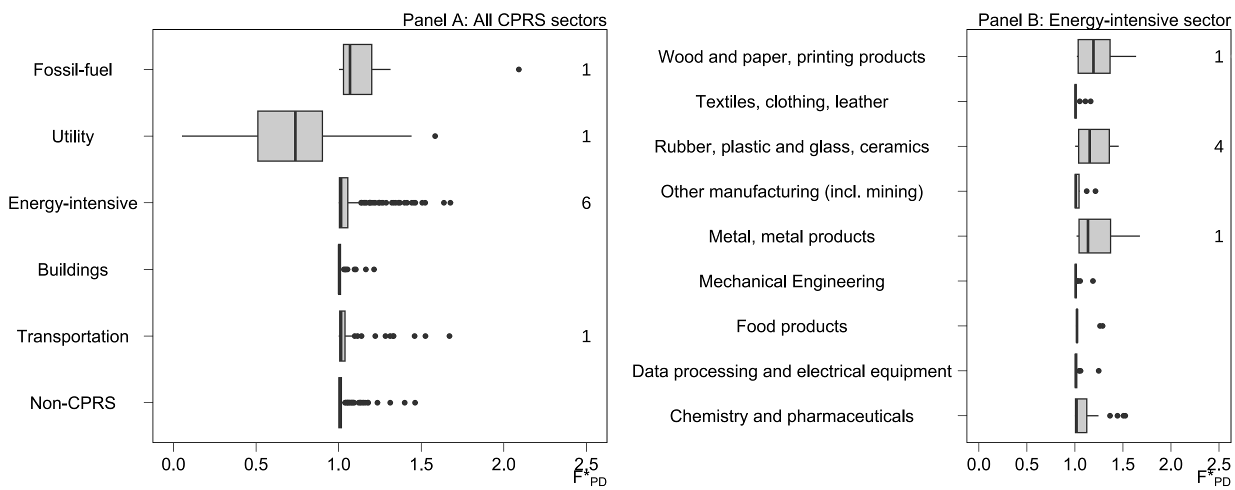


**Figure 7:** Impact, in terms of stressed PD factor $F^*_{PD}$, of the carbon shock in the enhanced stress scenario on firm creditworthiness, by sector. The boxes show the $25^{th}$, $50^{th}$ and $75^{th}$ percentile of the distribution, and the whiskers correspond either to the min or max, or to 1.5× interquartile range. The number of observations above the cut-off is indicated at the edge.

The results for the utilities sector suggest that creditworthiness improves significantly on average, driven by companies with more carbon-efficient technologies. This is because sub-marginal producers benefit from higher carbon prices due to the mechanism of price formation in the electricity market (Keppler and Cruciani, 2010; Hobbie et al., 2019). Our simplified model yields a revenue boost of 18.4% across the board for energy producers, whereas the total additional carbon costs sum up to 3.6% of total revenue. As evidenced by the European energy crisis in 2022, renewable energy suppliers do not see an increase in marginal costs while prices

[28] Table 8 in the Appendix shows detailed statistics on up- and downgrades

go up, driven by more polluting technologies. Our modeling of the pass-through mechanism is rather simple. Indeed, marginal cost pass-through and effective prices in the electricity market are highly dependent on the fundamental demand and supply structure (Chernyavs'ka and Gullì, 2008; Hobbie et al., 2019). Also, as shown in a report of the International Energy Agency (2022), companies' business models vary as firms may operate different technologies at the same time and engage in different contracts, which yields further complexity.

However, while the modeling remains simple to allow for an easy understanding of the quantitative impacts, it allows highlighting an interesting and somewhat counter-intuitive results. First, carbon pricing can be *financially beneficial* for carbon-efficient firms, which gives rise to *transition opportunities*. Second, the direct relationship between emission intensities and transition risk observed in the raw scenario vanishes on a cross-sectoral level in the enhanced scenario since utilities, having on average a higher emission intensity, are less exposed to carbon price induced credit risk. While the mechanism driving these results can be easily observed in the electricity sector, it could also occur in other sectors where technologies with different carbon intensities exist.

**Impact of using firm-level data**

In most countries, firms do not have to disclose their emissions following a standardized methodology and precise and comparable firm-level emission data are therefore often unavailable. Furthermore, standardized probabilities of default are available only for the largest firms. Therefore, when studying the impact of carbon pricing on firms, country-sector-level data tend to be used instead of the unavailable firm-level data.

To quantify the estimation error resulting from using country-sector-level averages instead of firm-level data, we compare the PD impact of the raw stress scenario for those firms where both data were available. Figure 8 shows the results, a scatter plot of PD impact using two methods: firm-level emissions data (x-axis) and sector average emissions (y-axis).[29] The impact

[29] The values on both the x-axis and the y-axis are derived using the ICAS model to obtain firm-level initial and stressed PDs.

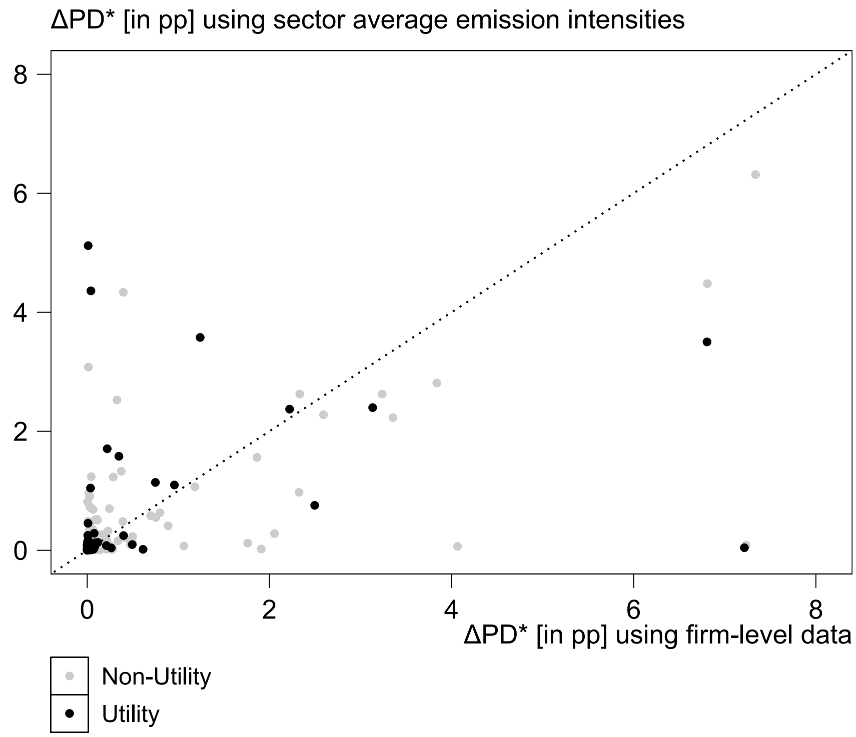


**Figure 8:** Scatter plot of PD impact $\Delta PD^*$ using two methods: firm-level data for initial PDs and emissions (x-axis) and sector averages (y-axis). The impact discrepancies between the more accurate use of firm-level data and the country-sector-level approximation are significant.

discrepancies between the more accurate use of firm-level data and the sector-level approximation are significant. The average absolute deviation for the 776 firms is 0.19 pp, ranging from 0.03 pp in the sector buildings to 1 pp for utilities. The estimation errors in sectors with a wide range of emission intensities are particularly high. In the electricity sector, for instance, where different generation technologies co-exist, using the average sector-level emission intensity is inadequate both for low-intensity renewable and for high-emission coal-based firms, which is illustrated by the black dots in Figure 8.

## 4.2 Impact on bank capitalization ratios

In order to gauge the relevance for financial stability of the deterioration of firms' creditworthiness, this section translates the PD increases into changes of the capitalization ratios of euro area banks,[30] for both the raw and enhanced stress scenario, according to equation (5). Note that for the sample of 704 IFRS-groups we model the impact via firm-level data (for emissions and PDs) while for the rest of the firms we model the impact via simulated firm level emission intensities and the extrapolation model.

### Raw stress scenario

The histogram in Figure 9 presents the bank-level results under the raw stress scenario, i.e., mean impact on the CET1r. As a result of the stress, the aggregate CET1r of the banking sector decreases by 72 basis points (bps). This shock is manageable and comparable to the impact of the COVID-19 where the CET1-ratio decreased from 15.6% in Q4 2019 to 15.0% in Q2 of 2020. Given the harshness of the assumptions in the raw stress scenario, it is likely that the actual impact of an increase in global carbon prices would be even lower.

Figure 9 also shows that some banks are more significantly affected, with 19 banks experiencing a CET1r drop by 100 bps or more. These banks, however, have high unstressed capitalization ratios and the impact on CET1r in the raw stress scenario is not expected to lead to banks failing. In fact, only one bank drops below a CET1r threshold of 10% due to the stress.[31]

### Enhanced stress scenario

The histogram in Figure 10 presents the bank-level CET1r impact for the enhanced stress scenario, where we account for additional costs for Scope 2 emissions, already paid carbon costs and

[30] The sample consists of 81 bank groups (consisting of 570 banks) under the ECB's direct supervision for which the disclosure of the EBA transparency excercise and data from AnaCredit are available and which have a share of RWA for corporate credit risk of higher than 5%. For our sample of 776 IFRS-groups, the data set includes credit information for 704 IFRS-groups, encompassing a total of 4,370 firm-bank relationships to companies belonging to our IFRS-group sample. Additionally, the data set includes approximately 3.3 million firm-bank relationships to companies that do not belong to the IFRS-group sample.

[31] Two sample banks already start with a CET1r below 10%.

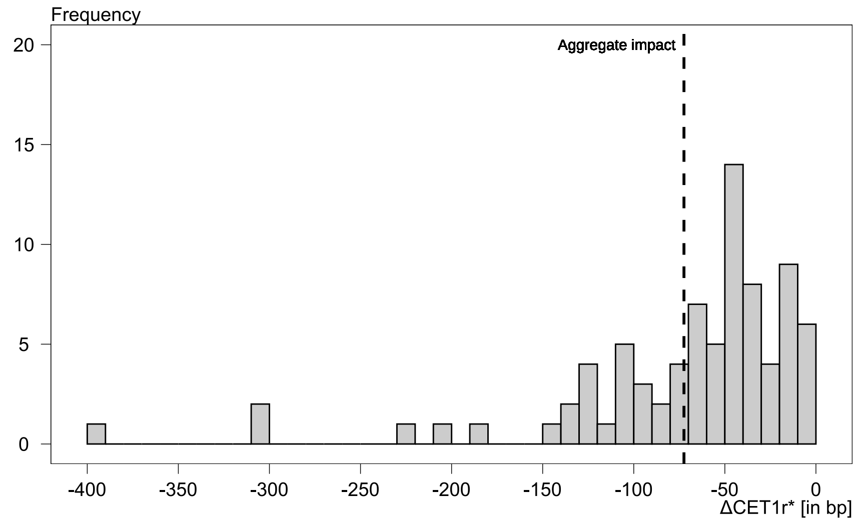


**Figure 9:** Histogram of the mean CET1 ratio impact per bank in the raw stress scenario.

increased revenue because of cost pass-through. Under this more realistic scenario, the stress is much lower than under the conservative raw stress scenario: the aggregate CET1r of the banking sector decreases by 19 bps, which is nearly negligible.

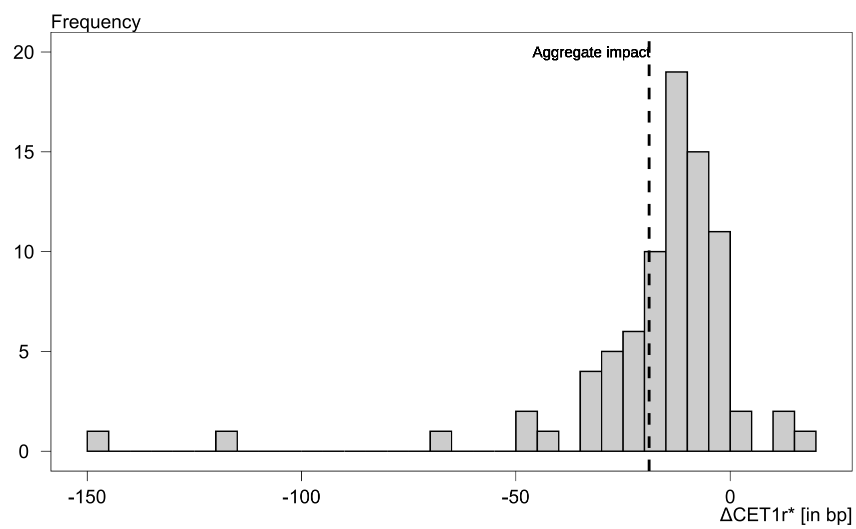


**Figure 10:** Histogram of the mean CET1 ratio impact per bank in the enhanced stress scenario.

In line with the change in PDs under the enhanced stress scenario (Figure 7), where several utilities see their PD *decrease* on the back of windfall profits, five banks see their CET1 ratio *increase* under this scenario. Consequently, not a single bank falls below a capitalization ratio of 10% due to the stress.

### Drivers of the CET1r impact

**Disentangling PD and staging effects** Higher PDs lead to both higher risk weights and credit risk provisions. The latter are affected by two mechanisms: first, higher PDs (and LGDs) lead to higher expected losses, second – according to the IFRS9 approach – exposures with a significant increase in credit risk (e.g. because of a significant increase in PDs) and impaired assets[32] need to be provisioned for lifetime losses rather than over a one-year horizon. All else equal, this second mechanism, the so-called "staging" effect, will further increase provisions and decrease CET1r.

In the analysis, exposures that experience a PD increase of a factor of 2 or more are reclassified into Stage 2 and require lifetime provision. On aggregate, the staging effect is small but non-negligible. Without it, the mean aggregate CET1r in the raw stress scenario would decrease by 51 bps (instead of 72 bps) and by 17 bps (instead of 19 bps) in the enhanced stress scenario.

What is more is that base PDs drive the stress on firms and banks. Even if the relative shock ($F^*_{PD}$) might be stable across the cycle as the shock does not depend on the financial position of the firm (see A.3.5), higher base PDs, e.g., due to a sluggish economy, will yield stronger impacts in terms of $\Delta PD^*$. Thus, the cyclical point of the economy also determines the stress impact via higher provisions and risk weights.

**Quantifying the effect of intra-sector heterogeneity of emission intensties** Figure 11 shows that accounting for the intra-sector heterogeneity of emission intensities by using simulated firm-level emission data leads to a higher impact $\Delta$CET1r* compared to the use of Eurostat

[32] Stage 2 and 3 exposures according to the IFRS9 nomenclature. Note that for in our analyses we do not consider Stage 3 moves but allow for strong PD shifts leading to credit risk provisions similar to a Stage 3 classification.

sectoral emission data for almost all banks in the raw and enhanced scenario. The same holds true for the results of 90% percentile in the raw and enhanced scenario. These differences are caused by firm-level data deviating from Eurostat sectoral averages and the nonlinear impact of CO2 price shocks on PDs, risk weights, provisions, and risk-weighted assets. In absolute terms the deviation is more pronounced in the raw scenario with four banks having a mean difference over 30bps. However, the relative deviation is nearly identical for the raw and the enhanced scenario with an on average 21% higher $\Delta$CET1r* impact in both scenarios.

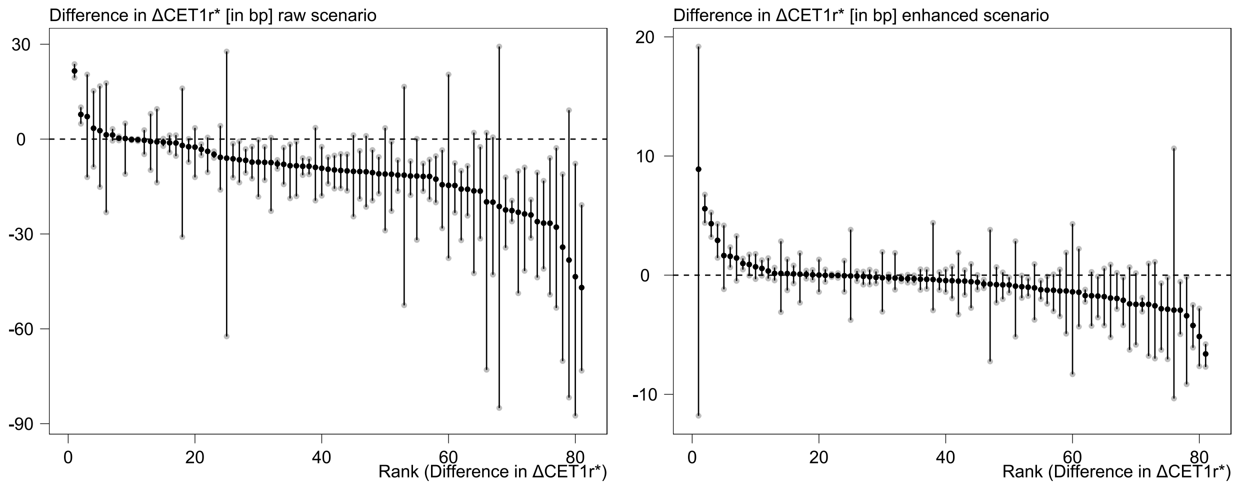


**Figure 11:** Difference between the stressed CET1 ratio impact $\Delta CET1r^*$ based on simulated firm-level emission intensities and based on country-sector Eurostat emission intensities in the raw (left panel) and enhanced scenario (right panel). The black dot corresponds to the mean difference, the bars represent 10% and 90% percentiles of the distribution. Bank results are ranked by the mean difference.

**Bank size** Bank size does not appear to be significantly associated with the mean CET1r* impact from a carbon price increase. Figure 12 displays the impact as a function of the (noisy)[33] rank order of corporate credit risk exposure for the raw stress scenario (left panel) and the enhanced stress scenario (right panel).

[33] By adding a random jitter to the rank order, individual banks' mean CET1r impact cannot be inferred from the graph.

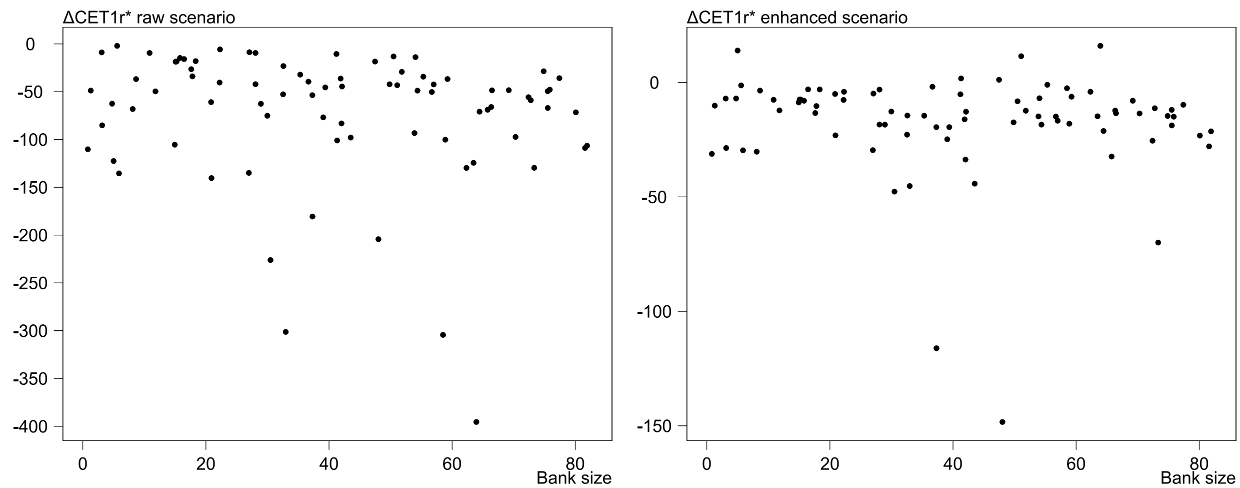


**Figure 12:** Mean CET1 ratio impact vs. bank size (rank order plus jitter in the raw (left panel) and enhanced scenario (right panel).

Setting aside those banks that are most affected (which are not among the biggest or smallest size quintiles), there is at best a small trend with bigger banks being on average marginally harder hit than smaller banks in the raw stress scenario. In the enhanced stress scenario, such a trend is not present.

**Portfolio emission intensity** Banks with higher portfolio emission intensities[34] tend to be hit harder by rising carbon prices. Figure 13 shows scatter plots of the mean CET1r impact versus portfolio emission intensity per bank for the raw stress scenario (left panel) and the enhanced stress scenario (right panel) highlighting banks with a considerable share of exposure to energy producers (over 10%) in their portfolio.

In the raw stress scenario, unsurprisingly, there is a strong negative relationship between a bank's portfolio emission intensity and its mean CET1r impact. This is to be expected as, in that scenario, PDs increase with firms' emission intensity[35]. These PD increases monotonously translate into a reduction of the bank's CET1r independently of the banks' exposure share of

[34] The exposure-weighted emission intensity of the firms in each bank's portfolio.
[35] See A.3.5

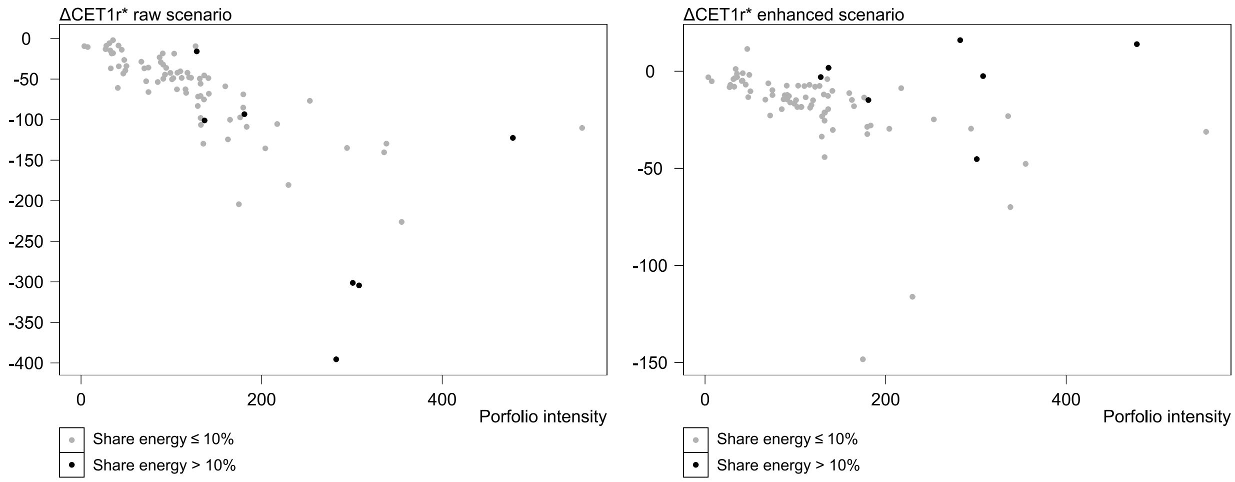


**Figure 13:** Mean CET1 ratio impact vs. portfolio intensity per bank. For comparability, we use the Scope 1 emission intensity on the x-axis for both scenarios. Banks where engergy producers account for over 10% of the exposure are shown in black.

energy producers.[36] Thus, emission intensities are a very good proxy of carbon transition risk, both at the level of firms and of banks' corporate lending portfolio. In this scenario, were banks to manage their carbon transition risk, they would impose stricter conditions on more emission intensive companies – such as higher interest rates and lower lending limits. They would thereby create financial-market incentives that contribute to decarbonization and apply above and beyond firms' incentive to avoid paying the carbon price itself.

In the (more realistic) enhanced stress scenario, we account for the market mechanics of the energy market leading to windfall profits for carbon-efficient producers.[37] Hence, the clear link between emission intensity and deterioration in credit quality vanishes at firm-level, indicating that emission intensities are no longer a good proxy for the short-term carbon transition risk. This is also observed at bank-level in Figure 13, where the negative relationship between portfolio emission intensities and the CET1r impacts disappears for banks with a high portfolio share in energy producers (exposure share ¿10%). Consequently, banks considering emission intensity as

[36]See A.3.3

[37]Pass-through rates are assumed to be higher in this sector, see Section 2.1, while the other firms bear these costs as Scope 2 emissions.

a proxy for transition risk and managing it via interest rates or lending limits may not always benefit cleaner firms compared to more polluting ones from other sectors.

### 4.3 Sensitivity analyses at the firm level

This section investigates how the modeling assumptions affect final results in order to gauge our conclusions' robustness.

#### Carbon price

The results are sensitive to the assumed carbon price increase. In summary, when assuming a higher increase in global carbon prices, the worsening of creditworthiness measured on the rating grades roughly scale proportionally with the carbon price increase, while PDs increase exponentially. Figure 14 shows that if the carbon price increases by EUR 200 instead of EUR 100, the stress in terms of $log(F^*_{PD})$ will be 100% higher on average. This translates into higher risk weights, higher provisions (with potential cliff-effects from the IFRS staging), and consequently deteriorates banks' capitalization metrics. It should be noted, however, that moving from a global carbon price of EUR 3 per $tCO_2$ (Parry, 2021) to EUR 200 is highly unlikely and that under such an increase, the underlying assumptions such as a no cost pass-through, static balance sheet structure, and the lack of a macroeconomic impact become more unrealistic.

#### Pass-through modeling

The impact of the stress on firms' creditworthiness scales roughly with the pass-through rate. Here, the same underlying model mechanics as for the carbon price applies, that is $log(F^*_{PD})$ decreases proportionally as the pass-through rate increases (see Figure 15). Furthermore, the simple pass-through scheme we apply for non-energy firms does not necessarily reflect how markets work. We model pass-through as a firm-by-firm revenue compensation of 50% of the firms' additional cost. Depending on the market structure, pass-through might also lead to net benefits for firms in industries other than energy production. Additionally, charging higher prices will also

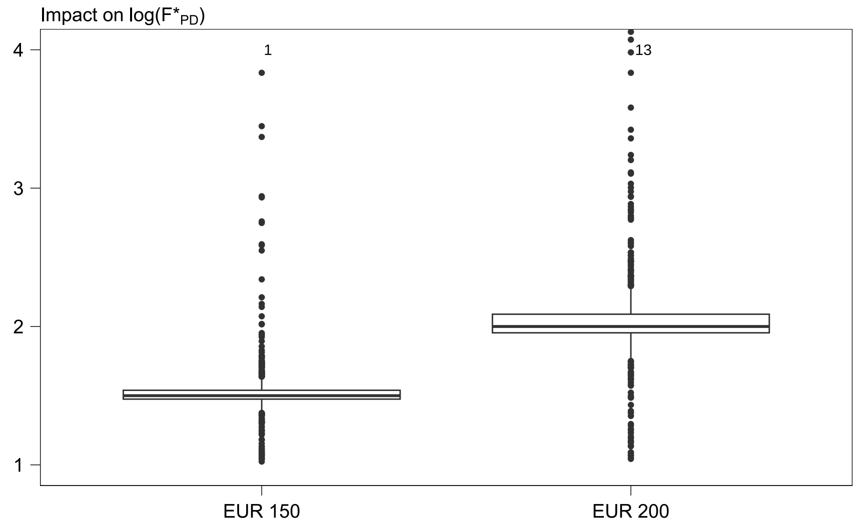


**Figure 14:** $\log(F^*_{PD})$ for a price of EUR 150 and EUR 200 relative to EUR 100 in the raw scenario. The boxes show the $25^{th}$, $50^{th}$ and $75^{th}$ percentile of the distribution, and the whiskers correspond either to the min or max, or to 1.5× interquartile range. The number of observations above the cut-off is indicated at the edge.

impact demand for firms' products.

### Financing additional carbon costs

While the results are very sensitive to the assumed carbon price increase and the modeling of firms' carbon cost pass-through, they are robust to the financing employed by companies to pay the carbon price, i.e., whether firms are assumed to run down cash reserves or borrow from banks to finance the additional carbon emission costs. The deviation between both approaches for for $F^*_{PD}$ corresponds to a negligible factor of 0.99 and 1.01 for the $5^{th}$ and $95^{th}$ percentile.

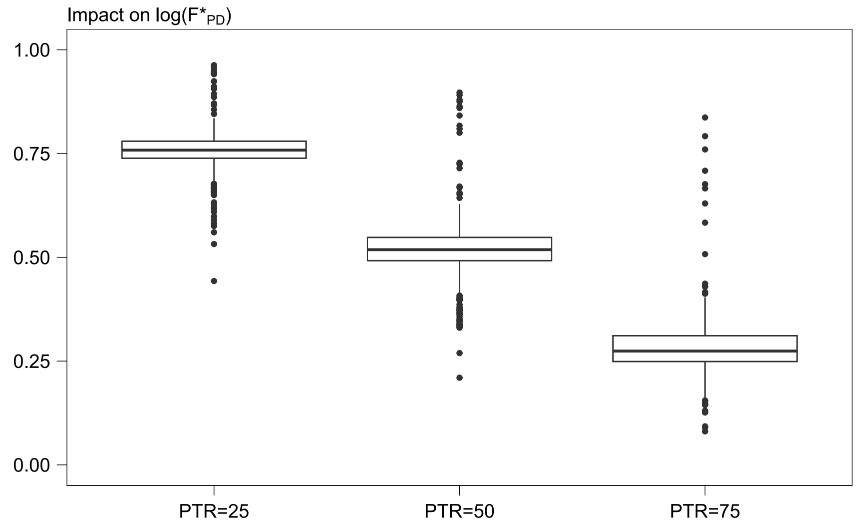


**Figure 15:** $\log(F^*_{PD})$ for different pass-through assumptions relative to a no pass-through situation in the enhanced scenario. The boxes show the $25^{th}$, $50^{th}$ and $75^{th}$ percentile of the distribution, and the whiskers correspond either to the min or max, or to 1.5× interquartile range.

# 5 Discussion

Carbon pricing is widely advocated as the most effective climate change mitigation policy. By affecting prices of intermediate and final goods according to their carbon content, it leads economic agents along value chains to bear the emission costs of the emissions they cause and thereby provides an incentive to reduce them.

While there is a broad agreement on the efficacy of carbon pricing, its negative fallout is often discussed, subsumed under the term "carbon transition risk". If implemented too abruptly, the argument goes, carbon pricing would wreak havoc in the economy, leading to widespread company bankruptcies, unemployment, and financial losses for investors. In this scenario, instead of improving welfare, carbon pricing would achieve the opposite. Quantifying the various transmission channels of carbon transition risk is therefore an essential ingredient for calibrating carbon pricing at a level that drives decarbonization while not endangering economic stability.

One kind of carbon transition risk is carbon pricing-induced credit risk, the potential negative impact of carbon pricing on firms' and households' ability to repay loans. In this research paper, we estimate this risk for a sample of 776 European non-financial firms and subject the over 2.5 million non-financial firms with loans at the 81 largest European banks to the same stress scenarios. Using a well-established probability of default (PD) model and the European credit register Anacredit, we quantify the carbon pricing-induced increase in firms' PDs and the impact on banks' capitalization ratio under two scenarios. We do not, however, account for the macroeconomic transmission channels of carbon pricing, as existing estimates in the literature vary widely and involve considerable uncertainty.

**Impact on firms**

We show that, even under the first – very conservative – scenario, in which the costs of global direct and energy-related emissions increase *by* EUR 100 per $tCO_2$ and firms are unable to pass on any costs associated with carbon pricing, a significant proportion of firms' PDs remains relatively unaffected. Indeed, 88% of firms are not downgraded, even by one notch. While some firms see a significant deterioration in their creditworthiness, the debt-weighted PD of the sample of 776 firms increases from 0.41% to 0.60%. We were surprised by this result: by assuming that the increase of prices by EUR 100 would be borne only by firms, we would have expected corporate creditworthiness to be substantially deteriorated. In reality firms would make consumers bear part of the cost and the impact on corporate credit risk will be even lower.

Indeed, under the second – more realistic – scenario, the costs of global emissions increase from EUR 3 *to* EUR 100 per $tCO_2$ and firms are assumed to pass on some of the carbon costs. Under that scenario, the impact on firms' creditworthiness is virtually negligible: the debt-weighed PD of the sample increases from 0.41% to 0.48%. Some of the cleaner firms actually *benefit* from a rise in carbon pricing and see their creditworthiness improve. Indeed, these firms face only very small additional carbon costs but earn a windfall profit from rising market prices. This underscores the existence of both *transition risks* and *transition opportunities* from carbon pricing.

### Impact on banks

In order to examine the broader financial stability implications, we quantify the effects of the carbon pricing shock on the capitalization ratio of the 81 largest European banks. In the conservative scenario, where firms are assumed incapable of passing on carbon costs to consumers, the aggregate Common Equity Tier 1 capital ratio (CET1r) is projected to experience a decline of 72 basis points, from 14.9% to 14.2%. This reduction, although non-negligible, is not expected to pose a systemic threat to the stability of the banking system. When considering a more realistic scenario where cost pass-through is feasible, the impact on CET1r is vanishingly small (17 basis points).

A number of recent research papers (Vermeulen et al., 2018, Alogoskoufis et al., 2021, Guth et al., 2021, Belloni et al., 2022, Aiello and Angelico, 2023, Emambakhsh et al., 2023, European Supervisory Authorities and European Central Bank, 2024) have also studied carbon-pricing induced credit risk of firms, although using different methodologies and coverage. The overarching conclusion across these analyses resonates with our own findings: the impact of carbon pricing varies by sector, yet its overall effect on both firms and financial institutions is expected to be manageable.

The aggregate macroeconomic effects of carbon pricing on variables such as output and unemployment remain uncertain, depending heavily on economic and methodological assumptions. These impacts, which could be either positive or negative, introduce an additional layer of uncertainty into the results. While it is acceptable to neglect these effects in a near-term analysis such as ours, the medium-term literature suggests structural shifts, with some sectors contracting as others expand. Capturing such dynamics would require a different study with significantly more assumptions. Therefore, our results are best understood as a near-term sensitivity analysis of carbon pricing impacts on firms' creditworthiness.

### Three policy recommendations

Our study suggests that the overall impact of a significant increase in global carbon pricing on European non-financial firms' creditworthiness and, consequently, on the capitalization of the euro area banking system, is anticipated to be generally manageable at this juncture. This observation indicates that significantly higher carbon prices do not endanger financial stability via the corporate credit risk channel in the short run – while long-term effects driven by firm-level reactions, macro-economic developments and related feedback effects and non-linearities, as well as policy reactions are beyond the scope of this analysis. When discussing the possible negative fallout of carbon pricing – this is the *first policy implication* – we should see credit risk only where it's due.

While we find the aggregate impact of a carbon-pricing shock to be manageable, this average conceals significant variation in impact between and within sectors. This differential impact is part and parcel of carbon pricing policies, which aim at having differing impacts on firms, contingent on their greenhouse gas emissions. Using the "Climate Policy Relevant Sectors" classification, we find that fossil fuel companies are much more affected on average than firms from the energy-intensive manufacturing, buildings, transportation and "non-climate policy relevant" sectors. Driven by different technologies, strong variations in the emission intensities and consequently the impact on the PD are observable within the utilities sector. At the bank level, we find that accounting for intra-sector heterogeneity of the emission intensity leads on aggregate to a 21% higher impact on the CET1r under both scenarios.

These important differences in impact between firms should not be ignored by banks and their regulators – this is the *second policy recommendation*. Indeed, many of the credit risk assessment methodologies – whether they rely on credit rating agencies or on models calibrated with historical time series – are backward-looking and might not differentiate between firms with varying emission intensities. In order to avoid significant losses, banks should therefore assess the forward-looking transition risk of their borrowers and do so at the firm-level, not simply relying on industry averages. They should then embed this assessment in their risk management practice, including pricing policies, limits, and origination standards. What's more, while the aggregate impact of a carbon-pricing shock on European corporates might be manageable, a bank whose loan portfolio is very concentrated in the most affected sectors and firms, might be hurt by rising carbon prices. Supervisory authorities should investigate such concentration risk and react appropriately [38].

Finally, we have shown in our study that firms' capacity to pass on carbon costs to their consumers is a crucial determinant of carbon pricing-induced credit risk. Further research is needed to capture the transmission of carbon-pricing signals all along the value chains, including demand elasticities, in order to better understand which firms will benefit and which will suffer from an increase in carbon pricing. Importantly, the amount of windfall revenues that firms can generate because carbon costs are passed through depends on market structures, is determined at the sector level and is not proportional to firms' emission intensities. Consequently, it is very likely that firms' and banks' carbon transition risk would *not scale with emission intensities* and managing that risk will not necessarily lead to polluting firms facing higher interest rates or the outright loss of financing.

The *third policy recommendation*, therefore, is to avoid treating emission intensities as the sole indicator for transition risk in analyses and to not overemphasize the role of the for-profit financial sector in accelerating the transition. Indeed, banks and funds will continue to finance projects based on their risk-return profile, which currently includes many high-emission ventures. Since the ability to pass-through carbon costs does not scale with emissions, even implementing a carbon price may not significantly alter this fact. While carbon pricing provides strong incentives to firms to reduce their emissions, this analysis indicates that the financial sector might not contribute to these incentives.

[38] Some regulators already formulate similar expectations, e.g., European Central Bank (2020)

# Declaration of Competing Interest

The authors report no potential conflict of interest.

# Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

# Acknowledgements

We want to thank Gerhard Winkler, Sabine Wukovits and participants in the OeNB research seminar as well as the workshop on "Climate change risk and credit assessment" hosted by Banca d'Italia (October 2021) and the MCM and ICD seminars at the International Monetary Fund for useful inputs and comments.

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# A Appendix

## A.1 Detailed firm-level statistics

Detailed firm-level statistics are given in Tables 4 to 8.

| CPRS sector | N | Investment-grade |
|---|---|---|
| Fossil-fuel | 16 | 81% |
| Utility | 45 | 76% |
| Energy-intensive | 236 | 67% |
| Buildings | 80 | 53% |
| Transportation | 92 | 59% |
| Agriculture | - | - |
| Finance | - | - |
| Scientific R&D | 11 | 0% |
| Other | 296 | 56% |
| Total | 776 | 60% |

**Table 4:** Distribution of sample companies and rating class by CPRS classification

| | N | min | p10 | p25 | p50 | p75 | p90 | max |
|---|---|---|---|---|---|---|---|---|
| Total | 776 | 1.00 | 1.00 | 1.00 | 1.01 | 1.03 | 1.23 | 57.89 |
| CPRS sectors | | | | | | | | |
| Fossil-fuel | 16 | 1.00 | 1.00 | 1.05 | 1.18 | 1.66 | 2.86 | 6.78 |
| Utility | 45 | 1.00 | 1.00 | 1.03 | 1.19 | 2.13 | 8.17 | 30.23 |
| Energy-intensive | 236 | 1.00 | 1.00 | 1.00 | 1.01 | 1.05 | 1.45 | 57.89 |
| Buildings | 80 | 1.00 | 1.00 | 1.00 | 1.00 | 1.01 | 1.03 | 1.17 |
| Transportation | 92 | 1.00 | 1.00 | 1.01 | 1.01 | 1.03 | 1.22 | 5.46 |
| Non-CPRS | 307 | 1.00 | 1.00 | 1.00 | 1.00 | 1.01 | 1.05 | 2.54 |
| Energy-intensive subsectors | | | | | | | | |
| Chemistry and pharmaceuticals | 42 | 1.00 | 1.00 | 1.00 | 1.02 | 1.11 | 1.40 | 2.85 |
| Data processing and electrical equipment | 54 | 1.00 | 1.00 | 1.00 | 1.01 | 1.01 | 1.02 | 1.59 |
| Food products | 9 | 1.02 | 1.02 | 1.02 | 1.02 | 1.03 | 1.85 | 2.04 |
| Textiles and clothing, leather | 25 | 1.00 | 1.00 | 1.00 | 1.00 | 1.01 | 1.04 | 1.17 |
| Mechanical Engineering | 45 | 1.00 | 1.00 | 1.00 | 1.01 | 1.01 | 1.02 | 1.14 |
| Metal, metal products | 17 | 1.01 | 1.03 | 1.04 | 1.10 | 1.80 | 11.02 | 12.16 |
| Other manufacturing (incl. mining) | 10 | 1.00 | 1.00 | 1.00 | 1.01 | 1.04 | 1.27 | 1.28 |
| Rubber, plastic and glass, ceramics | 22 | 1.00 | 1.00 | 1.05 | 1.24 | 1.88 | 45.94 | 57.89 |
| Wood and paper, printing products | 12 | 1.01 | 1.03 | 1.04 | 1.20 | 1.59 | 2.38 | 16.16 |

**Table 5:** Distribution of the stressed PD factor $F^*_{PD}$ across different sub-samples in the raw stress scenario

| | N | min | p10 | p25 | p50 | p75 | p90 | max |
|---|---|---|---|---|---|---|---|---|
| Total | 776 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.11 | 17.55 |
| CPRS sectors | | | | | | | | |
| Fossil-fuel | 16 | 0.00 | 0.00 | 0.01 | 0.03 | 0.14 | 0.79 | 3.84 |
| Utility | 45 | 0.00 | 0.00 | 0.01 | 0.06 | 0.40 | 1.83 | 7.21 |
| Energy-intensive | 236 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.21 | 17.55 |
| Buildings | 80 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 | 0.49 |
| Transportation | 92 | 0.00 | 0.00 | 0.00 | 0.01 | 0.03 | 0.19 | 7.34 |
| Non-CPRS | 307 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 1.06 |
| Energy-intensive subsectors | | | | | | | | |
| Chemistry and pharmaceuticals | 42 | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 | 0.11 | 0.80 |
| Data processing and electrical equipment | 54 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.04 | 0.20 |
| Food products | 9 | 0.01 | 0.01 | 0.01 | 0.02 | 0.03 | 0.09 | 0.28 |
| Textiles and clothing, leather | 25 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.14 | 0.47 |
| Mechanical Engineering | 45 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.21 |
| Metal, metal products | 17 | 0.00 | 0.01 | 0.02 | 0.08 | 1.76 | 2.33 | 2.59 |
| Other manufacturing (incl. mining) | 10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.06 | 0.06 |
| Rubber, plastic and glass, ceramics | 22 | 0.00 | 0.00 | 0.01 | 0.03 | 0.19 | 11.27 | 17.55 |
| Wood and paper, printing products | 12 | 0.00 | 0.01 | 0.01 | 0.03 | 0.25 | 0.73 | 1.91 |

**Table 6:** Distribution of the stressed PD difference $\Delta PD^{*}$(in percentage points) across different sub-samples in the raw stress scenario

| | | Downgrade | | |
|---|---|---|---|---|
| CPRS sector | N | >= one notch | >= three notches | to non-investment grade |
| Fossil-fuel | 16 | 50% | 6% | 15% |
| Utility | 45 | 53% | 20% | 35% |
| Energy-intensive | 236 | 17% | 4% | 8% |
| Buildings | 80 | 1% | 0% | 0% |
| Transportation | 92 | 9% | 2% | 2% |
| Non-CPRS | 307 | 4% | 0% | 1% |
| Total | 776 | 12% | 3% | 6% |

**Table 7:** Downgrades per CPRS sector in the raw stress scenario: downgrade by at least one notch, downgrade by three or more notches, and downgrade from investment grade to non-investment grade as a share of the sample size. The last column is computed as a share of firms starting with an investment-grade rating.

| | | Downgrade | | Upgrade |
|---|---|---|---|---|
| CPRS sector | N | >= one notch | to non-investment grade | >= one notch |
| Fossil-fuel | 16 | 25% | 15% | 0% |
| Utility | 45 | 9% | 3% | 69% |
| Energy-intensive | 236 | 16% | 4% | 0% |
| Buildings | 80 | 3% | 0% | 0% |
| Transportation | 92 | 9% | 2% | 0% |
| Non-CPRS | 307 | 4% | 1% | 0% |
| Total | 776 | 9% | 3% | 4% |

**Table 8:** Downgrades per CPRS Sector in the enhanced stress scenario. The "downgrade to non-investment grade" column is computed as a share of firms starting with an investment-grade rating. The last column presents the share of upgrades by one or more notches.

## A.2 Detailed bank-level statistics

Detailed bank-level statistics are given in Table 9.

| Variable | mean | min | p25 | median | p75 | max |
|---|---|---|---|---|---|---|
| CET1 ratio (%) | 16.79 | 8.40 | 13.47 | 15.66 | 18.24 | 37.97 |
| Portfolio intensity | 134.11 | 3.60 | 72.09 | 116.39 | 162.38 | 554.29 |
| Share corp. RWA (%) | 43.70 | 6.00 | 36.00 | 43.00 | 52.00 | 83.00 |
| Share IFRS-groups (%) | 6.13 | 0.00 | 1.68 | 3.93 | 8.42 | 32.15 |

**Table 9:** Statistics of main bank-level variables before the application of the stress

## A.3 Impact methodology

### A.3.1 At the firm level: raw stress scenario

In the raw stress scenario, firms' additional carbon costs are computed as

$$\Delta\text{costs} = 100 \times \text{global Scope 1 emissions.} \tag{6}$$

### A.3.2 At the firm level: Enhanced stress scenario

Equation (7) summarizes, how cost pass-through is modeled for different firms. Firms in the energy sector[39] are modeled separately and we account for cost pass-through via additional revenue,

$$\Delta\text{revenue} = \begin{cases} 90\% \times \Delta\text{carbon costs} & \text{most carbon intensive energy firm,} \\ F^{marginal} \times \text{revenue} & \text{other energy firms,} \\ 50\% \times \Delta\text{carbon costs} & \text{all other firms.} \end{cases} \tag{7}$$

where $F^{marginal}$ is defined as $\Delta$revenue/revenue for the most carbon intensive NACE 35 firm.

To summarize, firms' additional carbon costs in the enhanced stress scenario are computed according to equation (8)

$$\begin{aligned} \Delta\text{carbon costs} \;=\; & 100 \times (\text{Scope 1 emissions} + 90\% \times \text{ Scope 2 emissions}) \\ & - \underbrace{60 \times (\text{EU ETS emissions - EU ETS free allowances})}_{\text{EU ETS costs}} \end{aligned} \tag{8}$$

where EUR 60 per $tCO_2$ corresponds to the average price of EUA allowances in 2021. The overall costs (considering the pass-through to consumers) are given by equation (9):

$$\Delta\text{costs} = \Delta\text{carbon costs} - \underbrace{\Delta\text{revenue}}_{\text{cost pass-through}} \tag{9}$$

where $\Delta$revenue is given by equation (7).

### A.3.3 At the Bank Level

In order to calculate the stressed CET1 ratio, we split each bank's risk-weighted assets ($RWA$) in three parts:

[39] Firms operating in NACE classes 35.00, 35.10, 35.11, 35.12 35.13, 35.14 and 35.30.

- $RWA_{i,f}$ corresponds to the credit exposure of bank $i$ to a firm $f$ among the 776 firms described in Section 3.3 for which both financial statement and emission data are available $f$. Stressed $RWA$ and the increase in provisions for that exposure can be computed with few assumptions, detailed below.
- $RWA_{i,s}$ corresponds to the credit exposure of bank $i$ to all firms in sector $s$, excluding the 776 firms above. Stressed $RWA$ and the increase in provisions for this exposure can be computed with some assumptions, detailed below.
- $RWA_i^{other}$ covers all the RWAs that are not affected by the carbon-pricing induced credit risk stress, namely: market risk, operational risk, credit risk on exposures other than non-financial firms (households, financial corporations, the public sector, etc.)

For every bank $i$, we can then write the CET1 ratio as:

$$CET1r_i = \frac{CET1_i}{RWA_i^{other} + \sum_f RWA_{i,f} + \sum_s RWA_{i,s}}$$

and the stressed CET1 ratio as:

$$CET1r_i^* = \frac{CET1_i - \sum_f \Delta p_{i,f} - \sum_s \Delta p_{i,s}}{RWA_i^{other} + \sum_f RWA_{i,f}^* + \sum_s RWA_{i,s}^*}$$

Where $\Delta p_{i,f/s}$ is the change in credit risk provisioning for bank $i$ on firm $f$/sector $s$ and $RWA^*$ is the stressed $RWA$ after application of the carbon pricing shock.

The reminder of this section will describe how each of the data points needed to calculate the stressed RWA for each bank is obtained.

- $\mathbf{CET_i}$, $\mathbf{RWA_i}$, $\mathbf{RWA_i^{other}}$ The total amount of CET1 capital $CET_i$ and the total amount of risk-weighted assets $RWA_i$ and $RWA_i^{other}$ (the total bank RWA minus the RWA for total credit risk on non-financial firm) can be obtained from the EBA transparency exercise.
- $\mathbf{RWA_{i,f}}$ Risk-weighted assets for the 776 firms:
  - Exposure ($EXP_{i,f}$) is obtained via the gross carrying amount (GCA) in Anacredit.[40] As a first step, the list of banks within each significant institution banking group are derived. As a second step, using the ownership structures of borrowers, those firms belonging to the scope of consolidation of the 776 companies with emission and financial statement data are found. Based on these, it is then possible to obtain the exposure $EXP_{i,f}$ of bank $i$ to a firms $f$ among the 776 companies with emissions and financial statement data.
  - To obtain $RWA_{i,f}$ the risk weight computed with the Basel IRB formula (Basel Comittee on Banking Supervision, 2023), which takes an exposure-level PD and LGD as inputs.[41] In reality, some European banks do not use the IRB formula but the Standardized Approach (SA) to calculate risk weights. For all exposures that do not have

[40] GCAs for the 776 firms are taken as regulatory exposure value to which risk weights are then applied. They are not scaled to account for credit risk mitigation, off balance sheet exposure or specific provisions.

[41] $RWA_{i,f} = EXP_{i,f} \times RW(PD_f, LGD_{i,f})$

an external rating the SA risk weights are a flat 100 %. In line with other assumptions in this analysis, using the risk-sensitive IRB formula therefore overestimates the carbon pricing impact on banks.

- The firm-level initial probabilities of default ($PD_f$) are obtained with the ICAS model using firms' financial statements as inputs as described in Section 2.2.
- LGDs for each firm and sector are derived as described in the paragraph below.

- $\mathbf{RWA^*_{i,f}}$ Stressed risk-weighted assets for the 776 firms:
  - $RWA^*_{i,f}$ are obtained by applying the Basel IRB risk weights using stressed parameters $PD^*_f$ and $LGD^*_f$ to the initial exposure $EXP_{i,f}$.
  - The stressed probability of default ($PD^*_f$) is obtained with the ICAS model using firm's stressed financial statements as described in Section 2.2.
  - The stressed loss given default ($LGD^*_{i,f}$) is obtained using the approach by Frye and Jacobs (2012) which links long-run and point-in-time PD and LGD parameters. To that end firms' initial PD and LGDs are interpreted as the long-run parameters and the stressed PD as the point-in-time deviation from the long-run value. This allows inferring $LGD^*$.

- $\mathbf{\Delta p^*_{i,f}}$ Change in credit-risk provisions for the 776 firms:
  - To compute credit-risk provisions, we follow the IFRS 9 convention that unimpaired exposures (Stage 1) are provisioned over a one-year horizon, and impaired (Stage 2) and defaulted exposures (Stage 3) over the life-time of the loan. An initial Stage 1-exposures moves to Stage 2 if its PD more than doubles because of the carbon pricing shock. Our rating model does not assign a default rating class but (stressed) PDs may reach high values which imply Stage 2 provisions equivalent to Stage 3 provisions.
  - The change in credit-risk provision for the 776 firms is then computed by taking the difference between the stressed provisions (lifetime provisions in case of deterioration to Stage 2 or 3) and the initial provisions.

- $\mathbf{RWA_{i,s}}$ Risk-weighted assets for firms other than the 776:
  - Exposure is obtained via the Gross Carrying Amount (GCA) in Anacredit. For each significant institution, all outstanding exposures to firms that are not among the 776 is collected. For each exposure the NACE sector is known, so summing over all exposures yields $GCA_{i,s}$.
  - To obtain the prudential exposure value ($EXP_{i,s}$) to which the risk weights are applied, two further steps are applied:
    * First, using publicly available FINREP data from the EBA transparency exercise, for each bank $GCA_{i,s}$ is scaled such that the relative weight of each sector in each bank's portfolio corresponds to the weight in FINREP. If a bank has no exposure to a sector in Anacredit but does have exposure in FINREP, a dummy entry is added to the Anacredit information. Conversely if a bank has no exposure to a

sector in FINREP but does have exposure in Anacredit, the FINREP weights are adjusted.

* Second, keeping the relative weights of each sector fixed, the GCA of each bank is scaled such that the sum of GCA for that bank equals the prudential exposure value towards non-financial firms available via COREP. This accounts for credit risk mitigation, off-balance sheet exposures, provisions and exposures not in AnaCredit.

- As for the 776 firms, $RWA_{i,f}$ are obtained from applying the risk weights computed with the Basel IRB formula (which takes an exposure-level PD and LGD as inputs) to the regulatory exposure value of each of the (scaled) exposures obtained from Anacredit.
- PDs are obtained from Anacredit by using the reported PD of the exposure where available. If unavailable, an average PD by combination of country and sector is chosen and if that is unavailable too, the average sector PD is used.
- LGDs are obtained for each bank and sector ($LGD_{i,s}$) in two steps. In its benchmarking exercise (EBA, 2023), the EBA publishes sector-level average PD and risk weights (RW) by sector. Using the Basel formula, one can infer the average LGD per sector that, when combined with the average PD, matches the average RW. In a second step, keeping the relative values of LGDs by sector unchanged, all sector-level LGDs are scaled at the bank level such that, when combined with the actual exposure-level PDs (both for the 776 firms and all other Anacredit exposures) the obtained RWA for non-financial firms matches the bank-level RWA obtained via COREP.

- $\mathbf{RWA^*_{i,s}}$ Stressed risk-weighted assets for firms other than the 776:
  - $RWA^*_{i,s}$ are obtained by applying the Basel IRB risk weights using stressed parameters $PD^*_s$ and $LGD^*_s$ to the initial exposure $EXP_{i,s}$.
  - $PD^*_{i,s}$ is obtained using sector-level emission intensities from Eurostat and the regression analysis linking the ratio of stressed to initial PDs described in Section A.3.5.
  - The stressed loss given default ($LGD^*_{i,s}$) is obtained using the approach by Frye and Jacobs (2012) as described above for the 776 firms.
- $\mathbf{\Delta p^*_{i,s}}$ Change in credit-risk provisions for firms other than the 776:
  - For each Anacredit exposure $EXP_{i,s}$, the initial and final Stage is determined as for the 776 firms.
  - The change in credit-risk provision is then computed at the exposure level by taking the difference between the stressed provisions (lifetime provisions in case of deterioration to Stage 2 or 3) and the initial provisions.

### A.3.4 Monte-Carlo simulation for the firm-level emission intensity

We account for the within-sector heterogeneity of emission intensities in the bank portfolios by simulating a distribution of the firm-level emission intensity for each firm. Utilizing the firm-level data set, we calculate relative deviations to the mean sector emission intensity for every firm in the corresponding sector. To mitigate the influence of outliers, we implemented an upper emission intensity threshold to subsequently limit the resulting stressed PD factor to 50. For each of the 2.5 mio. borrowers in the credit register where no firm-level emission data are available, we draw 1000 times from these sectoral deviation factors and multiply the drawn factor with the corresponding country-sector average emission intensity available from Eurostat. Next we use this simulated firm-level emission intensity in our stress testing framework to calculate the bank-level metrics and we obtain distribution of these metrics for each bank. In the results we present the mean of this distribution.

In general, we utilize country-sector emission intensities on NACE 1-digit level from Eurostat. If no country-sector data are available for a borrower country, we rely on the EU-sector average from Eurostat. For the high-emitting subsectors of sections C and H we used emission intensities on NACE 2-digit level from Eurostat and for steel and cement production, we simulate emissions on the 4-digit level based on the firm-level data set. For NACE sections A and K there is no variation available since the firm-level data set does not include observations for these sectors.

### A.3.5 Extrapolating impacts

When simulating the PD impact on individual firms, we can establish a relationship between the stressed PD ($PD^*$) and firm-specific characteristics, such as the initial PD, the emission intensity ($EI$) and information on emissions paid under the EU ETS:

$$PD^* = f(PD, EI, EUETS) \tag{10}$$

Given the structure of the ICAS credit risk rating model and the stress scenarios, we expect an exponential relationship between the emission intensity and the stressed PD factor $F^*_{PD} = PD^*/PD$. We estimate a regression based on the 776 sample (see Table 10) for the scenario for a carbon price shock of EUR 100. For the enhanced stress scenario we regress $\log(F^*_{PD})$ to account for the windfall profits leading to an intercept lower than 0 for the energy sector. Using these regression models we can extrapolate the PD impact to firms and sectors for which we have no financial statement and no emissions but only PDs and (simulated) firm-level emission intensities. Figure 16 depicts the model fit of the extrapolation model for the raw scenario.

Table 11 shows that it is reasonable to assume that the relationship between the emission intensity and the PD shock also holds for other firms since essential determinants for credit risk such as the leverage, liquidity, profitability or firm size ratios have no additional statistically significant impact on the magnitude of the PD shock.

| Scenario | Raw | Enhanced non-energy | Enhanced energy |
|---|---|---|---|
| Dependent variable | $\log(F^*_{PD})$ | $\log(PD^*)$ | $\log(PD^*)$ |
| intensity | 0.0007*** | | |
| | (0.00002) | | |
| $\log(PD)$ | | 1.0009*** | 1.0104*** |
| | | (0.0015) | (0.0824) |
| non-paid intensity | | 0.0004*** | 0.0004** |
| | | (0.00001) | (0.0002) |
| paid intensity | | 0.0003*** | 0.0001 |
| | | (0.0001) | (0.0001) |
| constant | 0.0090** | 0.0096 | −0.5341 |
| | (0.0035) | (0.0086) | (0.4801) |
| Observations | 756 | 729 | 36 |
| $R^2$ | 0.6672 | 0.9983 | 0.8277 |
| Adjusted $R^2$ | 0.6331 | 0.9983 | 0.8116 |
| Residual Std. Error | 0.0906 (df = 754) | 0.0548 (df = 725) | 0.3120 (df = 32) |
| F Statistic | 1,511.7880*** (df = 1; 754) | 141,777.6000*** (df = 3; 725) | 51.2542*** (df = 3; 32) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 10:** Extrapolation models

| Dependent variable | $\log(F^*_{PD})$ | $\log(F^*_{PD})$ |
|---|---|---|
| intensity | 0.0007*** | 0.0007*** |
| | (0.00002) | (0.00002) |
| leverage | −0.0106 | −0.0047 |
| | (0.0151) | (0.0153) |
| liquidity | −0.0229 | −0.0081 |
| | (0.0295) | (0.0293) |
| profitability | 0.0426 | 0.0236 |
| | (0.0318) | (0.0330) |
| size_log(assets) | −0.0014 | |
| | (0.0017) | |
| size_log(revenue) | | 0.0025 |
| | | (0.0017) |
| constant | 0.0346 | −0.0217 |
| | (0.0263) | (0.0257) |
| Observations | 756 | 756 |
| $R^2$ | 0.6686 | 0.6692 |
| Adjusted $R^2$ | 0.6664 | 0.6670 |
| Residual Std. Error (df = 750) | 0.0906 | 0.0906 |
| F Statistic (df = 5; 750) | 302.6576*** | 303.4410*** |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 11:** Robustness of the extrapolation model in the raw scenario

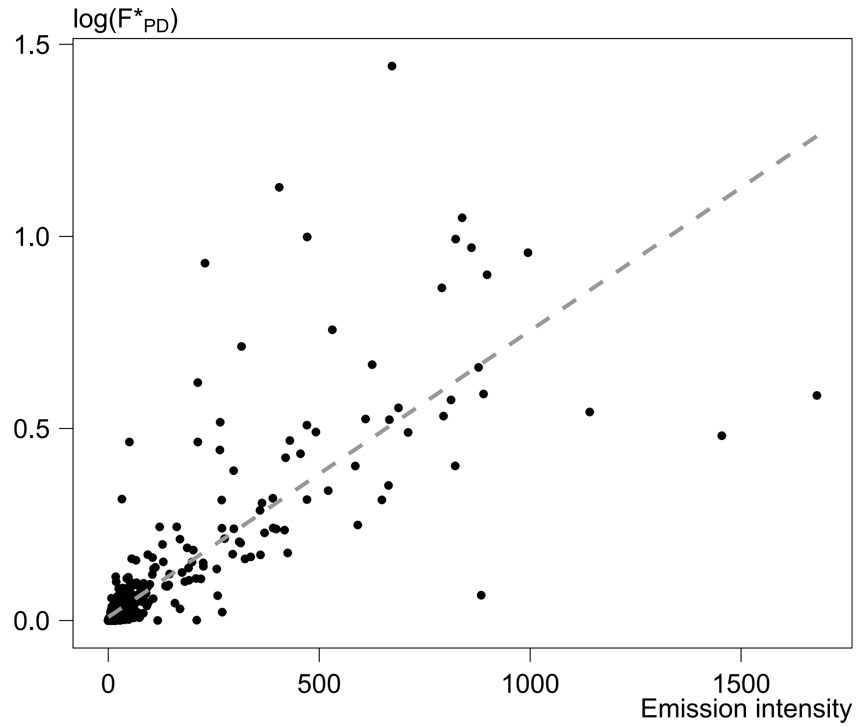


**Figure 16:** Model fit of the extrapolation model in the raw scenario.

| | Mean | Min. | 1st Qu. | Median | 3rd Qu. | Max. |
|---|---|---|---|---|---|---|
| Leverage | 0.38 | -2.61 | 0.26 | 0.38 | 0.51 | 0.97 |
| Liquidity | 0.15 | 0.00 | 0.06 | 0.12 | 0.19 | 0.92 |
| Profitability | 0.05 | -1.54 | 0.02 | 0.05 | 0.08 | 0.40 |
| log(Total assets) | 14.01 | 8.88 | 12.50 | 13.86 | 15.39 | 20.09 |
| log(Revenue) | 13.41 | 5.91 | 11.98 | 13.39 | 14.87 | 19.34 |

**Table 12:** Summary statistics of the control variables: Leverage defined as the ratio of equity over total assets. Liquidity defined as cash and bank deposits over total assets. Profitability defined as EBIT over total assets. Size as the logarithm of total assets and the logarithm of revenue.

PUBLICATIONS

Credit Risk Where It's Due: Carbon Pricing and Firm Defaults
Working Paper No. WP/2025/062