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Abstract

We develop a novel stress testing framework to quantify the risks to the German banking sector from the green transition. Our methodology combines a macro-level and a micro-level approach to calculate scenario-dependent probabilities of default and losses. The macro approach leverages traditional stress testing techniques in which aggregate scenario variables are translated into aggregate estimates of credit risk indicators. The micro approach uses firm-level balance sheet and carbon emissions data, allowing for the projection of heterogeneous effects across individual borrowers. Given that climate-related risks impact individual sectors and borrowers of the economy differently, exploring ways to quantify the distribution of potential effects is a key element of our framework. We find that potential losses over the near term from a green transition are non-negligible, highlighting that banks' loan portfolios are vulnerable to climate policy. Our estimates show that there are large differences across sectors and firms depending on their characteristics, most notably their carbon footprint, highlighting the importance of concentration risk in bank portfolios.

Keywords: climate-related risks, climate scenarios, stress testing, credit risk

JEL-Classification: C11, G21, G28, Q54, Q58

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1 Introduction

The potential impact of climate change on the global financial system has been attracting ever greater attention over the past years. Climate risks now rank as a priority issue for many central banks and supervisory authorities, prompting some to establish the Network of Central Banks and Supervisors for Greening the Financial System (NGFS), amongst other initiatives (Bolton et al. 2020; NGFS 2020). Changes in borrower solvency, asset recoverability and loan collateral induced by climate change can be detrimental to banks' new lending, profitability and stability. These effects may grow in force, impairing both the stability of the banking system and, via multi-round effects, the real economy (Zhou et al. 2023). Besides the direct economic impact of increasing extreme weather events, such as floods, droughts, storms or forest fires (physical risks), it has mainly been the risks associated with the need to transform the economy (transition risks) which have gained the most attention.

Capturing climate risks as appropriately as possible is therefore vitally important for assessing the stability of both individual credit institutions and the banking system as a whole (Battiston 2019). Because climate risks are a new phenomenon and much still needs to be done to fully describe and model their impact on banks, any effort to quantify these risks is fraught with significant uncertainty. Data availability issues combined with the extremely limited informative value of historical relationships between the likes of carbon prices, emissions and economic data complicate the task of developing and above all evaluating modelling approaches to quantify climate risks (Covas 2020; Baudino and Svoronos 2021).

Similar to other macroeconomic risks, stress tests are a fitting tool for analysing the impact of climate risks on the stability of the banking system. However, owing to the challenges mentioned above, conventional stress tests are not suited to assessing the negative impact of climate change on banks in an appropriate fashion (Bolton et al. 2020). It is therefore necessary to develop dedicated climate risk stress tests that adequately address the specific nature of these new types of risks.

The climate risk stress test presented in this paper makes two important contributions to the literature. First, unlike in previous studies, we examine a sample of banks that is both large (covering just under 1,300 banks) and highly heterogeneous, in a reflection of the idiosyncrasies of Germany's banking sector. The German banking system is based on three pillars, with private banks, including large international banks, existing alongside a great many regionally focused cooperative banks and savings banks. The regional principle according to which cooperative banks and savings banks usually run their businesses implies furthermore that those institutions' balance sheets should reflect the economic character of the region in which they operate. Moreover, the business model of regionally anchored banks is characterised by relationship lending, an approach built around longstanding ties between banks and their customers (Elsas and Krahnen 1998). Transition risks could take more of a toll on these institutions because their loan portfolio is less diversified and the long-term relationship lending approach could make it difficult to switch to borrowers that are not as vulnerable to climate risks. This backdrop means it is important for small and medium-sized regional institutions to be covered in climate risk stress tests.

The second major contribution our paper makes to the literature concerns the robustness of our model framework. By applying two standalone models (a micro approach and a macro approach) to translate stress scenarios into credit risk parameters, we cover a broader (model) spectrum and are thus able to estimate the uncertainty inherent in the models. These two approaches differ not just in terms of their fundamental modelling technique (a regression approach with assumptions-based modelling of corporate balance sheets vs. a regression approach using Bayesian model averaging), but also concerning the granularity of the calculations they produce (borrower vs. sector level).

Other climate risk stress tests have been conducted and published in the recent past by both academic researchers and other supervisory authorities (see Acharya et al. 2023 for an overview). The analyses cover different components of bank balance sheets, such as loans to firms or to households, and they model transmission channels via credit risk and/or market risk. Most approaches aim to quantify transition risks within a medium-term horizon (usually 3 to 5 years). Physical risks are modelled much less frequently. Exceptions can be found, inter alia, in Caloia and Jansen (2021) or in Mandel et al. (2021). While extreme weather events - such as floods and wildfires - have near-term consequences for banks, chronic hazards – such as increasing temperature-driven heat stress and sea level rise - materialise over very long horizons and depend on the stringency of climate policy today. The assumption that financial intermediaries' balance sheets remain static, which is standard procedure in stress tests, would impose a decisive constraint over such a long horizon, however.

Battiston et al. (2017) demonstrate in their climate risk stress test based on a network model approach that transition risks faced by banks very much depend on the timing of the policy measure and the expectations of market participants. Their stress test explores first-round and second-round effects, with the policy shock being propagated via the market risk channel in the financial system. Roncoroni et al. (2021) expand upon the climate risk stress test of Battiston et al. (2017) by adding the network valuation of financial assets (NEVA) approach as a way of analysing the impact of the interaction of climate policy shocks and market conditions on financial stability. The authors demonstrate that, given more favourable market conditions, more ambitious climate policy measures can be achieved with the same level of financial risk. Jourde and Moreau (2022) use securities issued by large European financial institutions to show that transition risks – unlike physical risks – have an increasing and significant impact on systemic risk in the financial market.

Vermeulen et al. (2021) assess different transition shocks and their impact on banks' exposure. Their model approach is inspired by the capital asset pricing model (CAPM) and uses input-output tables to break down the macroeconomic impact of shocks to economic sectors and bank-level exposures. Overall, they demonstrate that the portfolio loss at banks can be substantial. Grippa and Mann (2020) reach a similar conclusion, based on a sample of Norwegian banks, that transition risks are significant but manageable. Banks whose exposure is concentrated in high-risk sectors, i.e. sectors with a high level of emissions intensity, are particularly vulnerable. Reinders et al. (2023) investigate the impact of an abrupt spike in carbon prices on the Dutch banking sector. Using their valuation model at the economic sector level, they are able to show that the surge in the price of carbon significantly reduces the value of banks' assets in the markets. Jung et al. (2021) develop a stress test for transition risks as a basis for deriving a systemic risk indicator (CRISK). This indicator measures the expected capital shortfall following the materialisation of transition risks. Allen et al. (2020) analyse the long-term impact of transition risks on the French financial system up to 2050. Drawing on various model approaches, the authors break the NGFS scenarios down to sector and firm levels. They find that the impact of a disorderly transition to net zero on individual sectors and firms can be considerable, even if the impact on the aggregate economy and financial system seems limited. Likewise using a highly granular approach at the individual firm level, Emambakhsh et al. (2023) demonstrate that immediately and decisively implementing the transition to net zero could significantly reduce the risks to European financial stability from climate change.[1]

The analyses of Allen et al. (2020) and Emambakhsh et al. (2023) come closest to our paper. Much like these studies, we break macroeconomic climate scenarios down into sector and firm variables. This allows us to map heterogeneities in terms of vulnerability to transition risks. What distinguishes our approach from these studies is that we use a multi-layered analytical framework to translate climate scenarios into firm-level probabilities of default. This framework includes a great number of bridge equations to convert scenario-induced changes in macroeconomic aggregates, such as GDP, into changes in the (financial) situation of firms, as reflected in various balance sheet metrics. Since this granular breakdown of transmission mechanisms necessarily implies making numerous assumptions, e.g. regarding firm behaviour, we would like our estimates to visualise the breadth of possible impacts on credit risk. Instead of making simple point estimates, our approach delivers, for each firm, multiple variants of estimation results for the projected probability of default, allowing us to make

[1] The same conclusion is reached in the 2022 bottom-up climate risk stress test of the Bank of England (2022).

statements on the dispersion of the results and thus model uncertainty. Applying two fundamentally different model types (a micro model and a macro model) yields additional insights into the breadth of possible results. Our paper therefore represents an effort to quantify, by means of a stress test exercise, the high degree of uncertainty surrounding the transition to a low-emission economy.

Our results show that, for the transition scenarios under analysis, probabilities of default rise on average by as much as 40% for non-financial firms over the three-year horizon in question.[2] Heterogeneity across sectors and firms is substantial. While emissions-intensive firms are exposed to significantly stronger increases, those producing less emissions see hardly any uptick in credit risk. Cumulative credit losses required over the horizon as a result of rising credit risk come to between around 0.23% and 0.36% of the originated loan volume.[3] While overall sizeable, credit risk losses from transition risk are smaller compared to estimated losses from recent stress tests using general adverse macro scenarios.[4] Our results suggest that climate transition risks in isolation may be classified as manageable, it is – nevertheless – important to highlight that these are always additional losses that would place extra strain on banks during possible economic or financial crises. Another point worth noting against the backdrop of pronounced heterogeneity in Germany's banking sector is that losses may turn out to be significantly higher at certain less diversified institutions.

The rest of this paper is structured as follows. Section 2 discusses the data and scenarios. Section 3 introduces the model framework, comprising the micro and macro approaches used to translate the stress scenario into credit risk parameters. Section 4 describes the empirical findings for probabilities of default in each scenario and for the credit losses. Section 5 concludes.

2 Data and scenarios

2.1 Supervisory, financial and climate-related data

This paper draws on data from various sources, some of which are linked for the purposes of the analysis. Table 1 provides an overview of the data used; detailed information on variable definitions and data sources can be found in the Appendix (Table A1 and Table A2). The key indicator of credit risk used in the analysis is the probability of default (PD) disclosed by German banks in the context of supervisory reporting.[5] Banks using internal risk models

[2] Probabilities of default start out at a low level of 0.39% (median PD).

[3] These losses would incur on top of an approximated aggregated starting value of 0.51% (PD x LGD x EAD).

[4] The most recent Bundesbank supervisory stress test for Less Significant Institutions (LSIs) reports additional loan loss impairments on corporate loan exposures of 0.6% in the adverse scenario (Deutsche Bundesbank 2024).

[5] Alternative data on PDs is available from private data providers, which is typically limited to large and listed firms. However, a large proportion of German banks' corporate loan exposure is to small- and medium-sized enterprises, limiting the validity of any results relying on alternative PD data.

(internal ratings-based approach; referred to as IRBA banks) are required to report a PD as a risk metric for each of their bank-firm credit relationships.[6] Many non-IRBA banks report PDs on a voluntary basis. For the micro model, we use the reported firm-level PDs; where multiple PDs are reported for one borrower, we take the median value. In the macro model, we aggregate firm-level PDs from supervisory reporting to the level of the sectors (NACE 2-digit) using volume-weighted mean values. In our analysis, we exclude the financial sectors (NACE 64-66), the public sector (NACE 84) and households (NACE 97).[7] We therefore consider a total of 50 sectors. We restrict our analysis to German banks' domestic loans, hence excluding foreign borrowers.

In order to calibrate historical elasticities, it is also necessary within the framework of the econometric models used to link PDs to explanatory variables for general economic developments. In the macro model, we use publicly available macroeconomic time series for Germany on gross domestic product (GDP), short and long-term interest rates, equity prices, inflation, the unemployment rate and the European carbon price. In the micro model, firm-level time series for the return on assets, the liquidity ratio, leverage, interest expense and the equity ratio are used as explanatory variables (see Table A1 for sources). The carbon price enters the micro model only in the scenario period to project firm-level balance indicators based on bridge equations, but it does not enter as explanatory variable in the PD regressions.

Data on the volumes of bank-firm credit relationships are needed to weight the projected PDs and calculate the credit losses. We obtain these from firm-level information on outstanding volumes, which individual banks are required to submit in reports to the German credit register maintained by the Bundesbank.

Finally, we use granular firm-level data on greenhouse gas (GHG) emissions for the micro model. To this end, we use European Union Emissions Trading System (EU ETS) reporting. The EU ETS obliges firms in certain sectors to buy allowances for the greenhouse gases they emit. For this purpose, firms must measure their absolute emissions; the data are verified by an independent body and then published at the industrial installation level. For this analysis, the data were aggregated at the installation operator level. We complement ETS data with emissions from the European Pollutant Release and Transfer Register (E-PRTR), a public database in which absolute emissions data for the EU and five other countries from more than 30,000 industrial facilities (for comparison: around 11,000 in the EU ETS) covering 65 economic activities are reported. Unlike EU ETS data, the data in the E-PRTR are already published aggregated at the firm level. We also use data from ISS (Institutional Shareholder

[6] There is a total of 29 IRBA banks, including all Significant Institutions (SIs) (as at January 2024).

[7] We focus on the non-financial corporate sector, as the direct emissions of financial corporations are low. A carbon price shock therefore has hardly any direct impact on the solvency of these firms; instead, it only affects them through changes in the credit risk contained in their portfolios. The public sector and households are not modelled due to data limitations. Granular emissions data at the household and public administration level are not available.

Services), a commercial data provider supplying information on the absolute GHG emissions and emissions intensities of around 25,000 firms worldwide. For all other firms for which no firm-level emissions are available, we use sector-level emissions data from Eurostat.[8]

As there is no standard identifier in the various microdata sources, data are initially matched based on commercial register number and section as well as the location of the local court. In the second step, any firms left over are linked by name and postal code. In order to optimise matching success based on firm names, a complex process of name normalisation using 200 rules was carried out beforehand. For example, certain terms and characters that appear in firm names were harmonised (e.g. AG changed to "Aktiengesellschaft"), superfluous spaces were removed (e.g. AG instead of "A G") and all letters were switched to uppercase. After completing the linking process and removing firms with fewer than three observations in the period 2008-20, our sample contains a total of 17,881 individual firms that also appear as borrowers in the credit register.[9] For the calibration of elasticities between PDs and balance sheet indicators or macroeconomic variables by means of panel regression (see Section 3.1), we use the period 2008-19. NFC balance sheet information from 2020 is combined with the PDs from Q4 2022, with the result that this point in time also acts as a starting point for the scenario-dependent projections.

Table 1: Data overview

Type of data	Macro model	Micro model
Historical data for probabilities of default	Sector-level PDs based on reporting in Bundesbank's credit register	Firm-level PDs based on reporting in Bundesbank's credit register
Historical data for explanatory variables of econometric models	Macroeconomic time series from public sources: GDP, short and long-term interest rates, inflation, equity prices, unemployment rate, carbon price	Firm-level balance sheet indicators from Bundesbank database of annual financial statements: return on assets, liquidity ratio, leverage, interest expenses, equity ratio
Banks' exposure to non-financial corporate credit	Total nominal credit amount outstanding for all German bank-firm pairs as at 2022 Q4	
Carbon emissions data	Historical carbon price at aggregate level (ICE Intercontinental Exchange for EU allowances)	Firm-level: European Union Emissions Trading System (ETS), European Pollutant Release and Transfer Register (E-PRTR), ISS ESG Carbon Data Sector-level: Eurostat

Note: See Table A1 and Table A2 for further details on the data.

[8] We use the following hierarchical approach for assigning emissions data to individual firms: EU ETS > E-PRTR > ISS ESG > Eurostat. Due to significant data gaps, only around 10% of the outstanding volume of corporate loans can be covered using firm-level data. However, these firms are responsible for around 85% of the direct GHG emissions by German firms.

[9] The period covered by the linked dataset is contingent on data availability. The Bundesbank's credit register has existed since 2008. At the same time, firms' annual financial statements are only published and transferred to the database with a time lag, which is why 2020 is the latest year with sufficient data available at the time this analysis was being performed.

2.2 Climate scenarios

Two different transition scenarios are considered for the analyses: the NGFS "Net Zero 2050" scenario, which simulates an orderly transition to a climate-neutral economy by 2050, and a short-term stress scenario in which a jump in the carbon price to €200 is assumed. We compare both transition scenarios with the respective baseline scenarios of no transition taking place ("Current Policies")[10].

The "Net Zero 2050" scenario is one of the scenarios provided by the NGFS (third vintage),[11] which was disaggregated by sector and calibrated for Germany on the basis of Frankovic (2022).[12] "Net Zero 2050" envisages an orderly transition to global climate neutrality by 2050, which in turn will lead to achieving the 1.5°C target under the Paris Agreement. It is used as the stress scenario in our model framework. Serving as a comparison or baseline scenario is "Current Policies NGFS" calibrated for Germany, which assumes the continuation of current global climate policies. The NGFS scenarios map the period from 2022; in this analysis, the full projection horizon is based on the starting point defined above (see Section 2.1). While the horizon of the NGFS scenarios covers the next few decades, this analysis focuses on the first three years to accommodate the assumption of static bank balance sheets.

In addition, a short-term scenario (STS) is used as an alternative. The STS and the corresponding baseline scenario ("Current Policies STS") map pathways of macroeconomic variables for Europe, which are also broken down to economic sector level. The STS is based on a DSGE model,[13] with the central assumption of the adverse scenario being a sudden (and permanent) increase in the carbon price to €200. In contrast to the NGFS scenario used, a complete economic transformation is not modelled, as the scenario design focuses on the short-term impact of a sharp increase in the carbon price.

How the key macroeconomic variables develop in the simulated scenarios can be seen in Figure 1. The effects of the carbon price shock are reflected in the macroeconomic variables primarily in the first few years,[14] and GDP growth rates converge again over time in the baseline and stress scenarios. Looking at equity prices, the shock is especially persistent in the NGFS scenario. In addition to the variables depicted, other macroeconomic variables from the scenarios are used, such as long-term interest rates, inflation and unemployment.

[10] Comparing the transition scenarios with the respective baseline scenarios where no transition is taking place should be understood as a conservative approach, as in reality, the economic transformation has started. In theory, our approach could be used to compute effects from other type of climate transition scenarios as well.

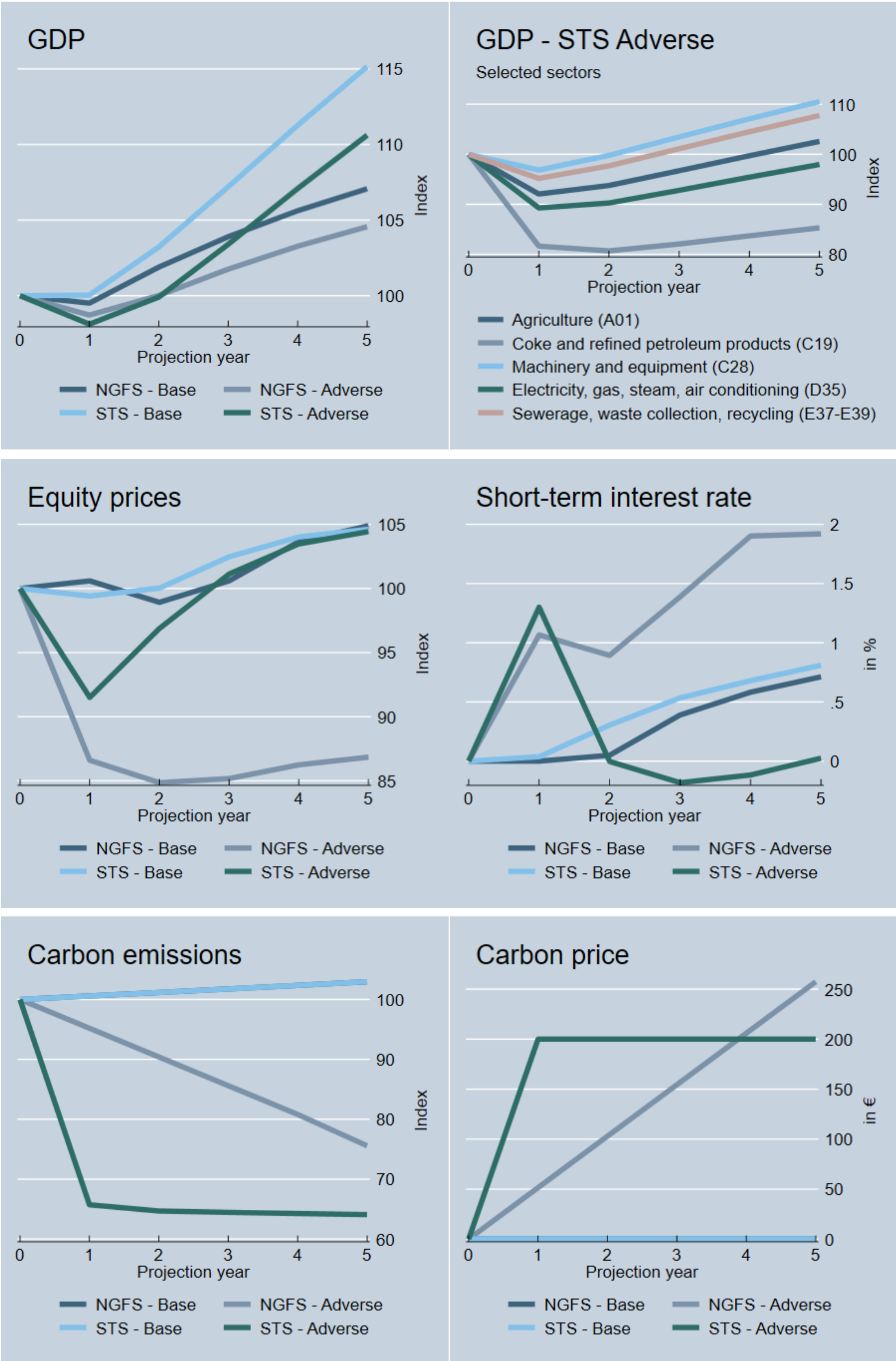
[11] It should be noted that the NGFS describes and views its own approach and the derived scenarios as exploratory. With that in mind, these types of scenarios are not "conventional" (adverse) stress test scenarios that are determined based on historical observations (such as economic crises).

[12] A production network model is used for sectoral disaggregation, see Frankovic (2022).

[13] For an explanation of the DSGE model used, see Frankovic and Kolb (2024).

[14] In the adverse STS, a negative shock occurs in the first few quarters in particular, which is also reflected in negative growth rates (at a quarterly frequency). However, a rapid recovery means that annual growth rates quickly turn positive again.

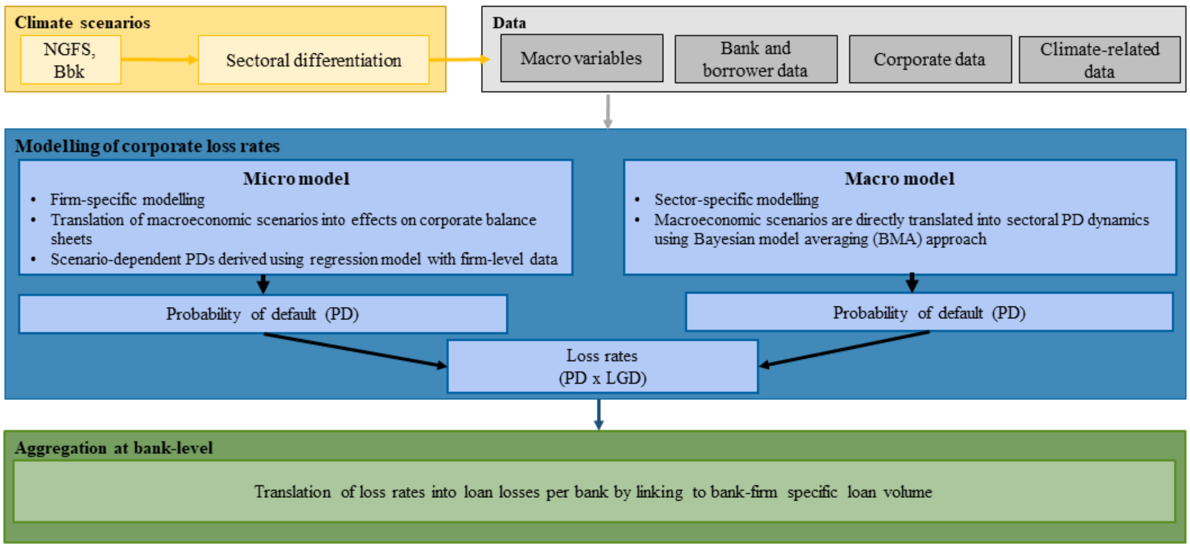
Figure 1: Selected scenario variables



3 Modelling framework of the climate risk stress test

The climate risk stress test developed in this paper comprises various model building blocks that translate the scenarios into changes in PDs of loans to the corporate sector. What makes our analysis unique is the application of two complementary methodological approaches, which differ in the granularity of the data used and in the modelling methodology. First, we use a micro approach based on granular firm-level data, in which scenario-dependent PDs are calculated at the level of individual firms. To achieve this, we model the impact of scenarios on the financial statement metrics of individual firms, taking a number of modelling variants into account. This means that the approach departs somewhat from the usual extrapolation and scaling of historical relationships. Second, we use a macro approach, in which the methodological framework functions very much like conventional top-down stress tests, and which calculates scenario-dependent PDs at the level of economic sectors. Figure 2 provides a stylized overview of our modelling approach.

Figure 2: Overview of modelling approach



3.1 Micro-level approach

The aim of the micro-level approach is to take account of the expected heterogeneity in the transmission of climate risks to the economy in the modelling. First, a panel regression framework is used to analyse the PDs at borrower level with regard to their dependence on balance sheet and P&L metrics.[15] The borrowers' balance sheet and P&L metrics are then

[15] Panel regression frameworks are an established technique in stress testing. In most cases, the approaches are based on bank-level data (Covas et al. 2014; Kok et al. 2019; Gross et al. 2021), but recently models based on data at the level of corporate borrowers have been proposed (Tressel and Ding 2021).

projected on the basis of the climate scenarios. Finally, the borrowers' PDs are derived by applying the estimated coefficients of the panel regression model to the projected balance sheet and P&L metrics.

3.1.1 Econometric framework

In general terms, the model can be expressed as follows:

$$PD_{i,t} = \beta_0 + \beta_k X_{i,t} + FE_s + \varepsilon_{i,t}. \quad (1)$$

$PD_{i,t}$ represents the logit-transformed PD of firm i in year t ($t = 2008, \dots, 2019$) based on reporting in the Bundesbank's credit register. The vector $X_{i,t}$ contains key financial metrics commonly used in the context of corporate credit risk assessments. We consider the following metrics: return on assets (ROA), the leverage ratio, the liquidity ratio, the interest expense ratio and the equity ratio (see Table A1 in the Appendix for further information).[16] All variables are winsorised (at the 1/99% level) to reduce the impact of outliers. The vector $\beta_k = (\beta_1, \beta_2, \dots, \beta_k)$ comprises the estimated regression coefficients, which represent the empirical effect of the five balance sheet and P&L metrics ($k = 1, \dots, 5$) on borrowers' PDs. To control for sector-specific effects, the regression equation takes industry fixed effects FE_s into account (subscript s denotes *sector*); in further specifications these are interacted with time fixed effects (industry-year) in order to test for robustness.[17] Based on the estimated parameters $\widehat{\beta_0}$, $\widehat{\beta_k}$ and $\widehat{FE}_s$ and the scenario-dependent values for $X_{i,t}$, we derive projected paths for firm-level PDs, $\widehat{PD}_{i,t}$. For borrowers with missing data points, we use median values of the projected PDs at the sector level.

3.1.2 Econometric results

Table 2 displays the results of the regression in equation (1). Column (1) shows the baseline specification. All coefficients are significant and have the expected sign. ROA is negatively correlated to the development of PDs. A deterioration in firms' profitability increases their PD. Leverage is positively correlated with credit risk, which is consistent with the mechanism that a higher level of debt limits firms' repayment ability. A higher proportion of liquid funds

[16] One could argue that equity ratio and leverage ratio are substitutes, because they are inversely correlated. However, according to German reporting standards equity and liabilities are not the only positions on the liabilities side in firms' balance sheets. Other positions include provisions, deferred income and special items, all of which cannot be easily assigned to equity or liabilities in a clear-cut way. Liabilities as used in our analysis are defined in a narrow sense and comprise almost exclusively loans from other parties. Changes in other positions and transfers between them and equity or liabilities are the reason why leverage and equity ratio are not perfectly correlated. Statistically, we find a moderately high correlation coefficient for leverage and equity ratio of 0.79. We also checked if our regression results are in any way distorted by the inclusion of both leverage and equity by running two separate regressions in which only one of the ratios are utilized. The results do not yield substantial deviations compared to our baseline specification.

[17] For the specification of industry fixed effects, we use the same sector classification as for the scenario variables for gross value added, i.e. a total of 50 economic sectors, broadly corresponding to the two-digit NACE2 codes (see Section 2.2).

acts as a buffer for firms and is therefore associated with lower PDs. Higher expenditure on debt service, which is reflected in a higher interest expense ratio, is associated with greater credit risk and thus higher PDs. Finally, the results show that higher equity (in relation to total assets) is associated with lower PDs.

Table 2: Regression results for balance sheet drivers of firm-level PDs

	(1)	(2)	(3)	(4)
ROA	-0.094***	-0.094***	-0.126***	-0.126***
Leverage	0.108***	0.114***	0.112**	0.118***
Liquidity ratio	-0.081***	-0.081***	-0.088***	-0.088***
Interest expense ratio	0.204***	0.196***	0.190***	0.181***
Equity ratio	-0.063**	-0.059***	-0.063**	-0.058***
Fixed effects	Industry	Industry-year	Industry	Industry-year
Lag structure	t	t	t-1	t-1
Obs.	93,385	93,385	69,966	69,966
Adj. R^2	0.195	0.203	0.210	0.218

*Notes: The table shows the results of the panel regression model as detailed in equation (1). The dependent variable is the logit-transformed PD of firms based on data from the Bundesbank's credit register. Reported estimates result from standardised coefficients (all variables have zero mean and variance 1). Results in columns (1)-(4) are based on different specifications with respect to fixed effects (industry or industry-year) and lag structure (contemporaneous, t, or lagged, t-1, regressors). Standard errors are clustered at industry-year level. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.*

In columns (2)-(4), we implement some variations in our baseline specification to test the robustness of the econometric model. First, we interact industry fixed effects with year fixed effects to additionally control for unobserved time-varying effects at the sector level. The results in column (2) suggest that the impact on the individual parameters is small. As expected, R^2 increases slightly when additional regressors are taken into account. In columns (3) and (4), we test the impact of the lag structure on the results by lagging all variables on the right-hand side by one year instead of using contemporaneous regressors. This also leads to only minor changes in the coefficients. Based on these robustness tests, we select the baseline model in (1) as the underlying specification for the projection horizon.[18]

[18] The estimated time-invariable industry fixed effects in model (1) are adopted for the projection horizon. Opting for one of the models with interacted fixed effects (industry-year) in (2) and (4) would make it difficult to project the time effects in a meaningful way. Estimating future time dummies would only be feasible if additional structure were included in the model; this would, however, entail greater model uncertainty (Baltagi 2021). Using the model with industry fixed effects and lags of explanatory variables (column (3)) as baseline for projections would come at the cost of fewer available observations, and hence fewer projections for individual firms. This would run counter to our ambition of capturing climate risk at the most granular level possible.

3.1.3 Firm-level breakdown of macro climate scenarios

The results of the baseline specification in Table 2 are used to determine the impact of climate risks on borrowers' PDs. This involves modelling the impact of the climate scenarios on the individual firm-level metrics in vector $X_{i,t}$. Bridge equations are used to simulate how the macroeconomic developments depicted in the climate scenarios are reflected in micro-level terms, at the individual firm. For example, the changes in sectoral value added described in the climate scenarios are translated to firms' profitability, taking into account firm-specific carbon costs. Developments in short-term interest rates and equity prices also have an impact on the firm-level metrics. At the same time, the investment needed to fund the transition is modelled on the basis of a study by Burret et al. (2021).

The impact of the percentage change in the value added of sector s, $\Delta VA_s^{scenario,t}$, on the EBIT of sector s is calculated as follows:[19]

$$EBIT_s^{scenario,t} = F * (Sales_s^{scenario,t-1} * \left(1 + \Delta VA_s^{scenario,t}\right) - Cost_s^{scenario,t-1} * (1 + \Delta VA_s^{scenario,t} * c)). \tag{2}$$

F is the sensitivity of sales to value added shocks and is set to 1. This is consistent with the assumption that firms' sales develop in line with sectoral value added paths. The parameter c is the sensitivity of costs in relation to sales. We set c to 0.9[20] since firms have a certain amount of leeway in terms of adjusting their costs in response to a sales shock. On the other hand, owing to economies of scale, firms with growing sales may become slightly more profitable in the event of positive value added shocks.

In the observed scenarios, a shock to carbon prices negatively impacts the value added path. This will affect a sector by increasing cost, thus lowering EBIT. We assume that the shock to firms' cost will be, on the one hand, in line with their historic cost and, on the other hand, have more of an adverse impact on costs for firms with high emissions than for firms with low emissions. Therefore, the additional costs of sector s, $\Delta Cost_{s,}^{scenario,t} = Cost_s^{scenario,t} - Cost_s^{scenario,t-1}$, are distributed across the sector's firms not only in line with historical costs (i.e. firms do not just experience a cost shock equal to $\Delta VA_s^{scenario,t} * c$), but also according to firms' carbon emissions. The degree to which the additional costs in sector s are distributed according to firms' emissions rather than according to firms' historical costs depends on the extent to which, in the event of a carbon price shock, the value added of sector s is affected

[19] See similar approaches by Tressel and Ding (2021), Demmou et al. (2021) and Frankovic et al. (2023).

[20] Here we deviate from the value of 0.8 used in Demmou et al. (2021); in the context of largely positive value added shocks and thus sales shocks, our setting corresponds to a more conservative assumption. Analyses have shown that this assumption is not a strong driver of the results.

by direct emissions costs (first-round effects) rather than by second-round effects, because carbon costs are incurred for firms' direct emissions (Scope 1 emissions).[21]

The ratio of the change in value added from the first-round effect to the total change in value added of a sector is referred to as the first-round impact ratio $FRIR_s$:

$$FRIR_s = \frac{\Delta VA_{s,first}}{\Delta VA_s}. \tag{3}$$

$FRIR_s$ is used to break down the additional costs of sector s into additional costs stemming from first-round effects or direct emissions costs and additional costs arising from second-round effects or indirect effects:

$$\begin{aligned} \Delta Cost_s^{scenario,t} &= \Delta Cost_s^{scenario,t} * FRIR_s + \Delta Cost_{s,}^{scenario,t} * (1 - FRIR_s) \\ &= \Delta Cost_s^{scenario,t,first} + \Delta Cost_s^{scenario,t,second}. \end{aligned} \tag{4}$$

Additional costs of firm i from sector s are then calculated as

$$\Delta Cost_{s,i}^{scenario,t} = \Delta Cost_s^{scenario,t,first} * w_{s,i,emis}^t + \Delta Cost_s^{scenario,t,second} * w_{s,i,cost}^t, \tag{5}$$

where $w_{s,i,emis}^t$ is the weight of firm i within sector s in line with its share of the sector's emissions and $w_{s,i,cost}^t$ is the weight of firm i within sector s in line with its share of costs in the sector.

The impact of the shock to sectoral value added $\Delta VA_s^{scenario,t}$ on the EBIT of firm i is then

$$\begin{aligned} EBIT_{s,i}^{scenario,t} = Sales_{s,i}^{scenario,t-1} * \left(1 + \Delta VA_s^{scenario,t}\right) - Cost_{s,i}^{scenario,t-1} \\ + \Delta Cost_{s,i}^{scenario,t}. \end{aligned} \tag{6}$$

In other words, a value added shock, triggered by a carbon price shock, will affect a firm most if it is part of a sector that is highly impacted via first-round effects (high $FRIR_s$) and, at the same time, has high carbon emissions. But also firms that have high historic costs and are part

[21] Frankovic (2022) allows first-round effects to be distinguished from second-round effects when a carbon price shock is introduced. First-round effects refer to direct emissions costs calculated as the product of sectoral emissions and the carbon price. Second-round effects, on the other hand, refer to the general equilibrium effects that lead to price and demand changes in the production network. Second-round effects arise, for example, when an upstream sector increases its selling price, customers scale back their demand, or the firm itself decides to adjust its output or selling price. $FRIR_s > 1$ if the first-round effect of sector s is higher than the total effect of sector s. This is the case if the sector is able to pass on some of the carbon costs to downstream sectors. $FRIR_s < 1$ if second-round effects contribute to overall value added losses. This occurs, for example, if sector s is affected by higher costs for intermediate goods from upstream sectors or if it faces a sharp decline in demand.

of a sector that is strongly impacted by a value added shock via second-round effects (low $FRIR_s$) could be affected, independent of their direct carbon emissions.

The economic transformation of firms, i.e. the reduction of carbon emissions in line with the scenarios under analysis, requires a large number of adjustments, for example with regard to production processes or improving the energy efficiency of buildings. Investment is needed to achieve this. The study entitled “The contribution of green finance to achieving climate neutrality in Germany” commissioned by the Kreditanstalt für Wiederaufbau (KfW) provides information about the additional investment required in Germany – i.e. climate action investment beyond the investment that will be made in any case.[22] The study calculates the amount of additional investment required in various sectors in the period up to 2050 in order to almost completely achieve the objective of climate neutrality.[23]

We use the amounts of additional investment required for Germany identified in Burret et al. (2021) to approximate the annual incremental investment of the firms included in our analysis.[24] First, the additional investment amounts calculated in Burret et al. (2021) are scaled so that the annual incremental investment of sector s, $\Delta Invest_s^{scenario}$, only relates to the emissions considered in our sample. In some cases, additional investment from Burret et al. (2021) is also broken down further to the level of individual NACE sectors; in each case, this is done based on sectoral shares in the emissions of the sector aggregates considered in Burret et al. (2021). Sectoral incremental investment is distributed among individual firms in sector s based on the emissions weight $w_{s,i,emis}^t$ used above:

$$\Delta Invest_{s,i}^{scenario,t} = \Delta Invest_s^{scenario} * w_{s,i,emis}^t . \tag{7}$$

Based on the firm-specific changes in EBIT, investment, short-term interest rate changes and equity prices from the scenarios, we model the impact on the firm’s other balance sheet and P&L metrics such as debt, liquidity, equity, interest expenses and total assets. Further details can also be found in Appendix B).

In particular, it is assumed that firms take on more debt if the available liquidity is insufficient to cover liquidity outflows resulting from a negative EBIT or from interest expenses.

[22] See Burret et al. (2021).

[23] The climate action plan (CAP) scenario on which the study is based envisages an 87% reduction in emissions compared with 1990 levels by 2050. It is used by the Federal Government when drawing up its National Energy and Climate Plan (NECP) and is fully instrumentalised, meaning that the instruments needed to achieve the objective have been identified and are considered feasible from a societal point of view. By contrast, there is a “business as usual” scenario in which investment – in some cases climate action investment – is also made. In the study, additional investment is calculated as the difference between climate action investment in the CAP scenario and investment in the “business as usual” scenario. It amounts to an average of €45 billion per year.

[24] The required amounts of additional investment described in Burret et al. 2021 are directly applicable in the NGFS scenario because its objective is similar to that of the CAP scenario. In the STS scenario, however, the transformation is much more sudden – within the first three years emissions decrease by 36% instead of 14% (NGFS scenario). The amounts of additional investment required are thus multiplied by a factor of 2.6 in the STS scenario.

Incremental investment by firms, which is assumed to be fully debt-financed[25], also increases firms' debt year by year. Interest expenses are determined by the firm's debt level and the interest rate changes according to the scenarios. In order to keep firms' balance sheets as plausible as possible over the projection horizon, it is assumed that the debt and liquidity ratios at the beginning of the period under analysis correspond to the firm's target ratios. If a high level of excess liquidity, i.e. liquidity in excess of the firm-specific target liquidity ratio, arises as a result of favourable earnings developments, this is used to reduce debt. However, the firm-specific target debt ratio is also taken into account to the same extent so that debt levels do not fall too much.

To account for modelling uncertainty we use different modelling choices when translating changes in macro variables to firms' balance sheet metrics (see Table 3). The three areas where we assume ex ante that our modelling choices may impact strongly on results are (a) the year we use for initial values for balance sheet items, (b) the assumed payout ratio of firms (e.g. in the form of dividends) and (c) the calculation method of firms' equity. These variants are used to analyse whether our modelling choices strongly influence results (see Section 4.3.1).

Table 3: Overview of modelling choices in variants used for firm-level modelling

		Modelling choice 1	Modelling choice 2
A)	Initial values (initial balance sheet figures)	Only present	Including past values[26]
B)	Payout ratio	Payout ratio 40%	Payout ratio 80%
C)	Equity calculation	Micro: Firm-specific profits/losses increase/erode equity	Macro: Developments in line with sectoral equity scenario pathways

The different possible combinations of these modelling choices result in eight ($2^3 = 8$) different variants, i.e. a range of possible results per firm.

3.2 Macro-level approach

The macro approach of PD modelling is based on an established credit risk model known as the path generator. Based on historical dynamics between different macroeconomic variables and default rates, the path generator translates a macroeconomic (stress) scenario into PD paths using linear models and a benchmark constraint Bayesian model averaging (BCBMA) approach. The methodology underpinning the path generator is described in detail in Siemsen

[25] In order to maintain a conservative view we refrain from taking into account potential subsidies or other kinds of public support.

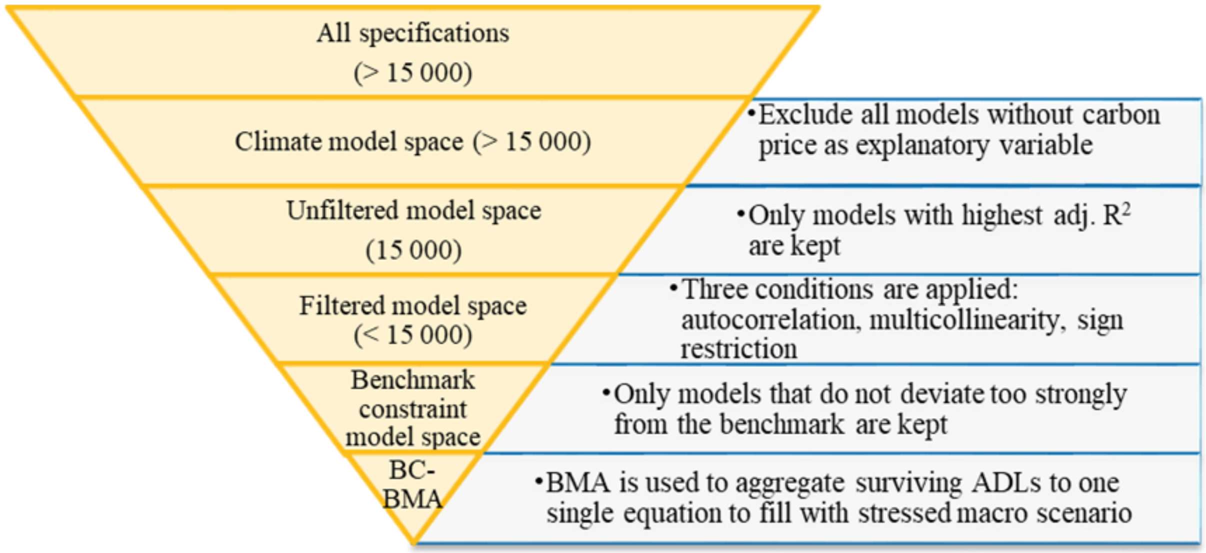
[26] Because the coronavirus crisis may have significantly distorted the most recently available annual financial statement data (2020), the two previous annual financial statements are included, equally weighted and in the form of a moving average, in variants with modelling choice A1.

and Vilsmeier (2018). The text below therefore only deals with the fundamental elements of the methodology and additionally explains the extent to which certain adjustments have been made for the purposes of the climate risk stress test.

3.2.1 Econometric framework

The relationship between PD and the macroeconomic scenario is established using a linear model. This is an autoregressive distributed lag (ADL) model estimated on the basis of ordinary least squares (OLS) assumptions. Various macroeconomic variables (including lags) feed into the model, as well as the lags of PD as the explanatory variable. As a general rule, forecasting models of this kind are extremely sensitive to changes in the model specification (e.g. due to a change in the macroeconomic variables considered), the exact variable specification (e.g. use of annual or quarterly growth rates) or changes in the data (e.g. a data history that grows longer and longer over time). The idea behind the path generator is to address this induced uncertainty, which is also amplified by incomplete data and potentially correlated variables. To this end, rather than defining one specification of the ADL model, an unfiltered model space is created. This contains all possible ADL model specifications as combinations of the macroeconomic variables, their lags and the lags of the dependent variable. The enormous number of individual ADL models in the unfiltered model space is reduced to the filtered model space by means of filter conditions, which are described in more detail below. After benchmarking, all remaining ADL models are merged into a model equation using a Bayesian model averaging (BMA) method. Figure 3 illustrates the different steps of the path generator.

Figure 3: Conceptual approach of the path generator with different filtering steps



In a final step, the PD paths are converted into what are known as add-ons. These add-ons separate the estimated development of the PD from the time series used in the estimation and can thus be applied to different PD starting values:

$$Addon_t = \Phi^{-1}(PD_t) - \Phi^{-1}(PD_0), \tag{8}$$

where Φ is the distribution function of the standard normal distribution.

The following specifications were made for the macro approach of the climate risk stress test:

- Corporate exposures are divided into economic sectors using the NACE classification. The maximum granularity here is limited by the granularity of the sectors in the Bundesbank's credit register. For some sectors of the economy, e.g. "manufacturing", this is the second level of NACE Rev. 2 (divisions) and for other sectors it is the first level of NACE Rev. 2 (sections).
- The carbon price is introduced as a binding[27] macroeconomic variable for carbon-intensive sectors so that the impact of the increased carbon price can be incorporated into the modelling of the credit risk parameters in a targeted manner for these sectors.[28] An overview of the sectors classified as carbon-intensive can be found in
- Table A3 in the Appendix.
- After the models have been estimated at the sector level, the scenario projections of the macroeconomic variables are applied in the estimated model equations to calculate the projected PDs. Sector-specific projections are used for the gross value added contribution in each case in order to be able to make the projection of the PDs as granular as possible.

The ADL model used in the climate risk stress test generally takes the following form:

$$\Delta PD_{s,t}^{log} = \sum_{i=1}^{K} \alpha_{s,i} \Delta PD_{s,t-i}^{log} + \sum_{i=0}^{L} \beta'_{s,i} \boldsymbol{x_{t-i}} + \varepsilon_{s,t}, \tag{9}$$

[27] In general, no assumption is made which macroeconomic variables build the final model. The selection is solely made by the model itself in accordance with the introduced filtering and benchmarking restrictions as well as the out-of-sample performance of every specification. However, we introduced a further restriction, namely that only those model specifications that include the carbon price (or its lags) are considered considered in the final model.

[28] While restricting the free selection of variables actually runs counter to the basic concept of the path generator, doing so takes account of the specific objective of the climate risk stress test. The implementation ensures that the scarce information about the scenario paths is used as best as possible and that the stress effect is translated to the probability of default in line with the scenario narrative.

where $\Delta PD_{s,t}^{log}$ is the first difference of the logarithmic PD at time t for sector s, and $\boldsymbol{x}$ contains the macroeconomic variables including their lags: GDP, long-term interest rate, inflation, unemployment rate, short-term interest rate, equity prices and carbon price (see Table A1 and Table A2 in the Appendix for further information). Both quarterly and annual growth rates of variables are used in the model. At the same time, the number of lags for the macroeconomic variables is restricted to four periods. To prevent the model from being reduced to a purely autoregressive model, the number of lags of the PD variables is restricted to two, while the total number of regressors per model is a maximum of four. The unfiltered model space contains all possible combinations of the variables and, in an initial step, is restricted to the best 15,000 models using the adjusted R^2. These 15,000 models are filtered based on the following conditions:

1. Autocorrelation:
   Only models that do not have significant autocorrelation in the residuals are taken into further consideration. This is evaluated using the Durbin-Watson test with a significance level of 10%.
2. Multicollinearity:
   The correlation between two macroeconomic variables in a model specification must not exceed 0.8. Models that do not meet this condition are excluded.
3. Sign restriction:
   The sign restriction relates to the long-run multiplier (LRM)[29] of each macroeconomic variable. A negative correlation with PD is expected for German GDP and equity prices. The correlation should be positive for long-term interest rates, carbon prices and the unemployment rate. No sign restriction is introduced for the LRM of the inflation rate and short-term interest rates, as the effect can be both positive and negative depending on the triggering event (demand or supply side).

All models that survive the filtering process are then evaluated for their stress test plausibility using a benchmark. This benchmark for the PD is derived from a Merton-Vasicek credit risk model.[30] Ultimately, all models that project a PD outside the interval around the benchmark PD are eliminated. The advantage of deriving the benchmark from an independent model class is that it smooths out potential distortions that may still be contained in the ADL model space due to the short time series history (e.g. a one-off, dominant crisis event). By using the Merton-

[29] The LRM is a standardised version of the regression coefficient. It indicates the expected change in the PD, measured in standard deviations, triggered by a one-standard-deviation change in the regressor.

[30] In this approach, PD depends on a systematic factor. Quantile mapping links the systematic factor to the macro time series and the benchmark PD is thus estimated based on the projections in the (stress) scenario.

Vasicek credit risk model, the benchmark estimation is not based on OLS assumptions. In this implementation of the path generator, all models whose estimated PD is more than two standard deviations (of the historical PD time series) from the benchmark are excluded.

Finally, the BMA algorithm links the filtered and benchmark-limited models by weighting them relative to their out-of-sample performance.[31] This aggregate model uses the variables of the macroeconomic scenarios described in Section 2.2. This means that the expected PD depends on macroeconomic developments. The coefficients for each macroeconomic variable and its lags are calculated as follows and consolidated into the projected change in PD:

$$\Delta PD_{s,t+j}^{log} = \sum_i \omega_{s,i}^{BMA} \cdot LRM_{s,i} \cdot \Delta PD_{s,t-i+j}^{log} + \sum_i \omega_{s,i}^{BMA} \cdot LRM_{s,i} \cdot x_{s,t-i+j} , \tag{10}$$

with j as the projection period, $x_{s,t-i+j}$ as the projection of each macroeconomic variable including lags, $\omega_{s,i}^{BMA}$ as the weight from the BMA for each model specification based on the out-of-sample performance and $LRM_{s,i}$ as the long-run multiplier for each variable. The annual difference of $\Delta PD_{s,t+j}^{log}$ is thus calculated.

3.2.2 Econometric results

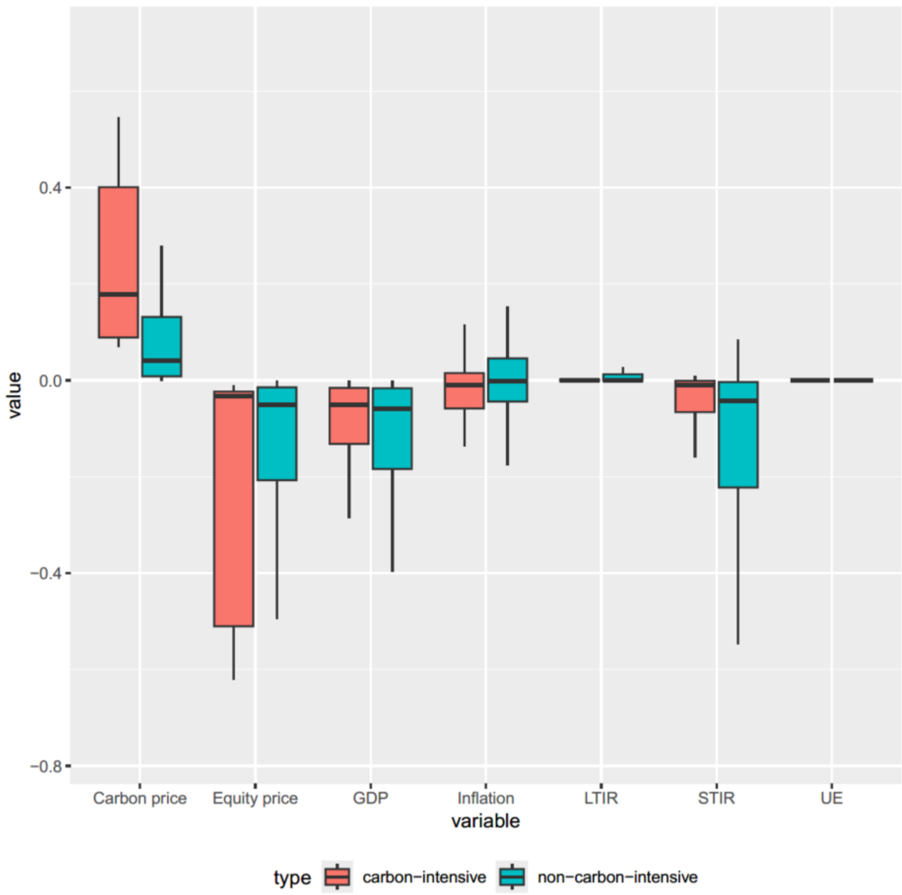
The distribution of empirically estimated LRMs is shown in Figure 4. At the horizontal level, a distinction is made between the macroeconomic variables x, on the one hand, and on the other hand, between (non-)emissions-intensive sectors per variable (according to the classification in Table A3). The box plots represent the distribution of the LRMs ($\sum_i \omega_{s,i}^{BMA} \cdot LRM_{s,i}$) aggregated using the BMA algorithm across the (emissions-intensive and non-emissions-intensive) sectors.

As expected, the LRMs for the carbon price, equity price, GDP, long-term interest rates and unemployment rate reflect the aforementioned sign restrictions in the path generator. The LRMs for the carbon price are generally higher in the models for emissions-intensive sectors than those for non-emissions-intensive sectors. The LRMs for short-term interest rates, which are not subject to sign restriction, are predominantly negative, with the respective LRMs of the models for non-emissions-intensive sectors (measured by various percentiles) being higher in absolute terms. Differences between sector groups are also evident in the LRMs for equity prices. The emissions-intensive sectors with the most negative LRMs are forestry, fishing, mining, manufacture of coke and refined petroleum products and energy. The LRMs for inflation are relatively evenly distributed in positive and negative terms and, like the LRMs

[31] If no models survive the filtering process for a specific sector, the benchmark estimation is used.

for GDP, hardly differ between sector groups. No clear distribution can be discerned for long-term interest rates and the unemployment rate. This is partly because the absolute value of the LRMs for these variables is, for the most part, lower than for the other variables. On the other hand, based on the filter criteria in Section 3.2.1, both variables are included less frequently as explanatory variables in the final BMA models per sector. For a detailed list of the individual LRMs per sector and variable, see Table A4.

Figure 4: Distribution of long-run multipliers across variables and sectors



*Notes: The figure depicts the distribution of long-run multipliers for all macroeconomic variables used in the macro models per sector. The upper whisker extends from the hinge to the largest value no further than 1.5 * IQR from the hinge (where IQR is the inter-quartile range, or distance between the first and third quartiles). The lower whisker extends from the hinge to the smallest value, at most 1.5 * IQR of the hinge. STIR = Short-term intervention rate. LTIR = Long-term interest rate. UE = Unemployment rate.*

3.3 Calculation of scenario-dependent PDs

The paths for PDs under the micro and macro approach are applied to the starting values of the credit risk parameters in the credit register of corporate loans using a non-linear transformation. As the dataset does not list a PD for every loan, the following procedural cascade is applied to fill the gaps in the starting values:

1. Use of the starting value reported for the respective loan (at borrower-lender level).
2. Use of the starting value reported for the borrower in question for other loans. Here, minimum, maximum, median and mean can be selected.
3. Use of sector PD. The value used can be either the minimum, the maximum, the median or the mean of the distribution of sector starting values.

The annual change in the PD in the stress test horizon is transformed into a distance-to-default (DtD), referred to as the add-on, for both modelling approaches (micro and macro approach). The borrower-specific (micro approach) or sector-specific (macro approach) stressed PD results from the retransformed sum of the loan-specific or sector-specific PD starting value (expressed as DtD in transformed form) and the corresponding add-on:

$$PD^{C}_{i,t} = \Phi\left(DtD_{i,o} + Addon_{i,t}\right), \text{ with } DtD_{i,o} = \Phi^{-1}\left(PD_{i,0}\right), \tag{11}$$

where Φ is the distribution function of the standard normal distribution. This non-linear transformation causes lower starting values to rise relatively more strongly than higher starting values.[32]

4 Results of scenario analysis

4.1 Aggregate results for scenario-dependent PDs

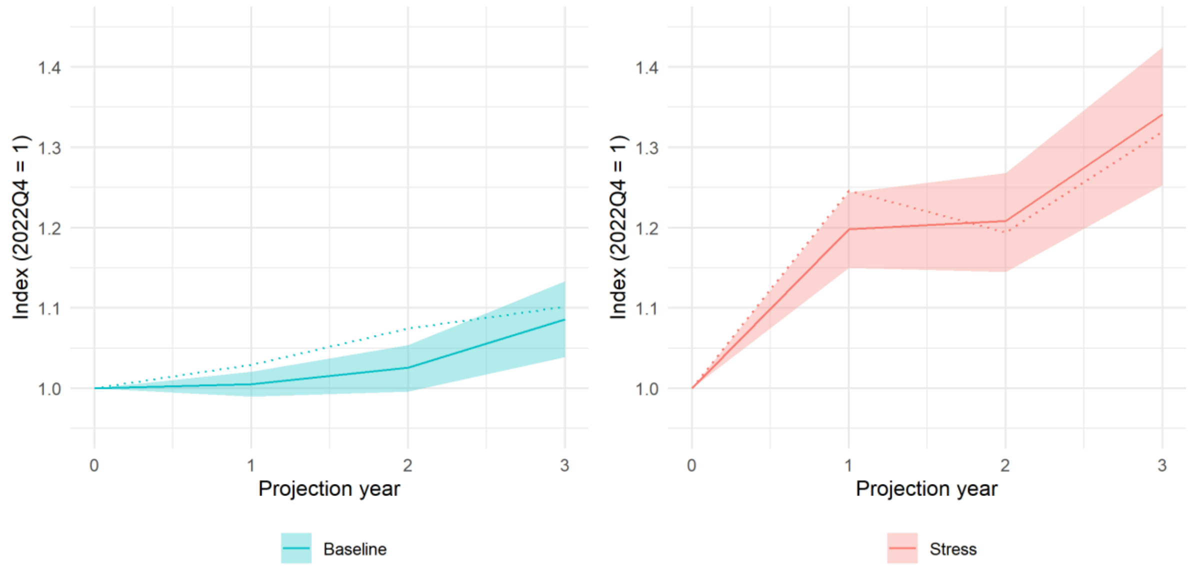
Figure 5 shows the results for the projected PD paths in the NGFS scenarios, aggregated across the entire German banking system. While the baseline scenario (left-hand chart) shows only a slight increase in PDs (by around 10% compared with the starting point after 3 years)[33], the increase in the stress scenario (right-hand chart) is substantial (by up to 40%). The estimations for the micro and macro models show similar trajectories and are of comparable quantitative magnitudes. In the stress scenario, the macro model's point estimator is consistently within the range of micro model estimations; in years 2 and 3 of the projection period it is even very close to the micro model's median value. In the baseline scenario, the macro estimation results

[32] The non-linear transformation helps to align different starting PDs for the same firm reported by different banks. The traceability of this approach is beneficial for our macro approach as there is no need for an expert judgement on the appropriateness of starting PDs.

[33] While the baseline scenario does not consider macroeconomic stress, it incorporates a moderate upward trend in interest rates over the scenario horizon. Higher interest rates increase firms' interest expenses in the micro model, which, in turn, lead to moderately higher PDs.

in the first two years suggest slightly higher PDs compared with the micro model, but the differences largely disappear in year 3.

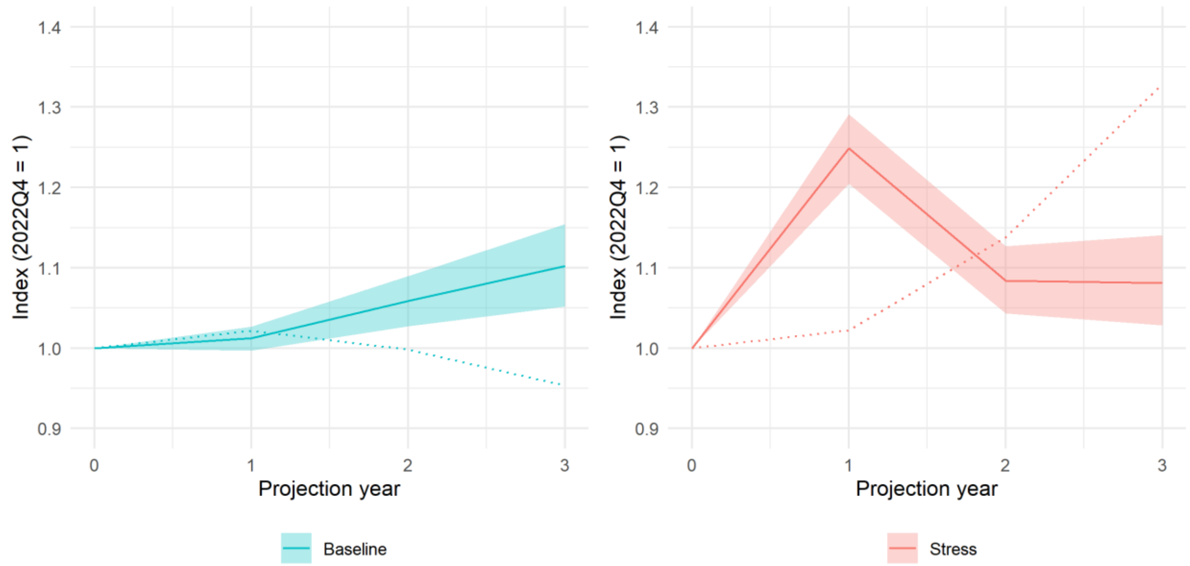
Figure 5: NGFS scenario – estimated PD projections at aggregate banking system level



Notes: The figure depicts the projected exposure-weighted PDs (expressed as multipliers with respect to the starting point) for the German banking system over the three-year stress test horizon for the Network for Greening the Financial System (NGFS) baseline and stress scenario, respectively. The dotted lines show weighted PD results for the macro model. Solid lines represent weighted PDs for the firm-level median estimates across the variants of the micro model; shaded areas show the corresponding min-max estimates.

Figure 6 shows the aggregated results for the short-term scenario (STS). In the baseline scenario (left-hand chart), PDs increase slightly in the first year in both model variants. While this increase continues in the following years in the micro model, PDs in the macro model come back down. In the stress scenario (right-hand chart), PDs increase by up to around 30%. However, the trajectories of the two model variants differ: while the maximum stress in the micro model occurs after just one year, it is only reached after three years in the macro model. This is largely due to the different influence short-term interest rates have in each case. In the macro model, a rise in interest rates is largely accompanied by lower PDs according to the regression coefficients (see Section 3.2.2). This is consistent with the notion that interest rates are driven by strong economic growth and not by supply shocks, causing PDs to fall. By contrast, in the micro model, higher interest rates are associated with higher PDs (see Section 3.1.2) because firms' interest expenses rise. As short-term interest rates in the STS initially jump higher in the first year, before coming back down in the following years in response to falling inflation and recessionary developments, PD increases in the micro and macro models correspondingly behave differently.

Figure 6: STS scenario – estimated PD projections at aggregate banking system level

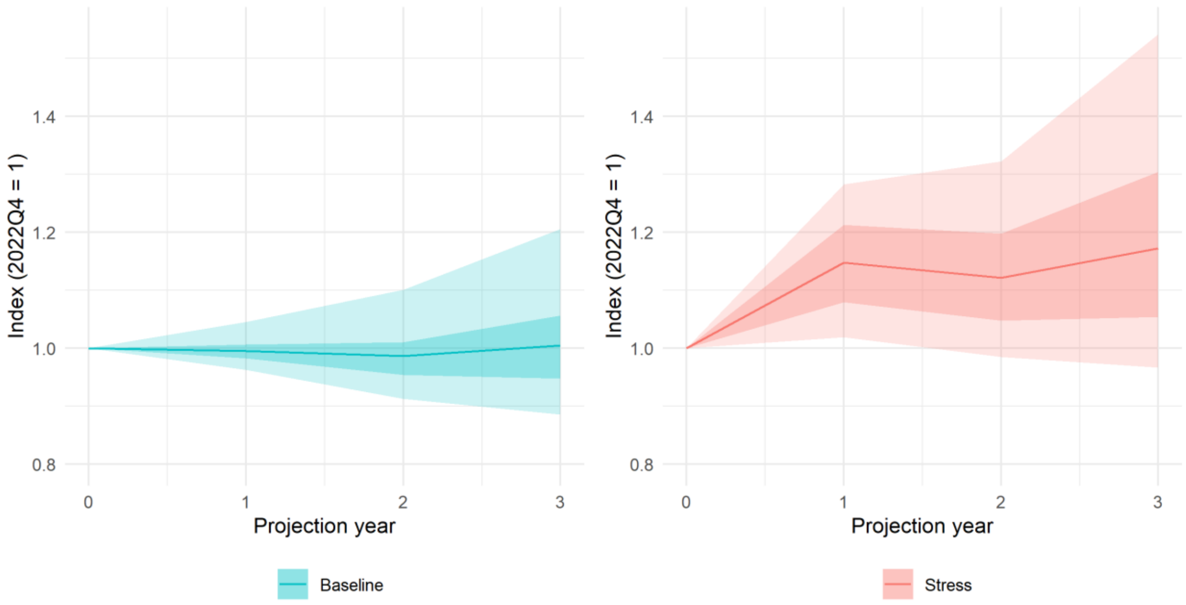


Notes: The figure depicts the projected exposure-weighted PDs (expressed as multipliers with respect to the starting point) for the German banking system over the three-year stress test horizon for the Short Term Scenario (STS) baseline and stress scenario, respectively. The dotted lines show weighted PD results for the macro model. Solid lines represent weighted PDs for the firm-level median estimates across the variants of the micro model; shaded areas show the corresponding min-max estimates.

4.2 Heterogeneity across sectors and firms

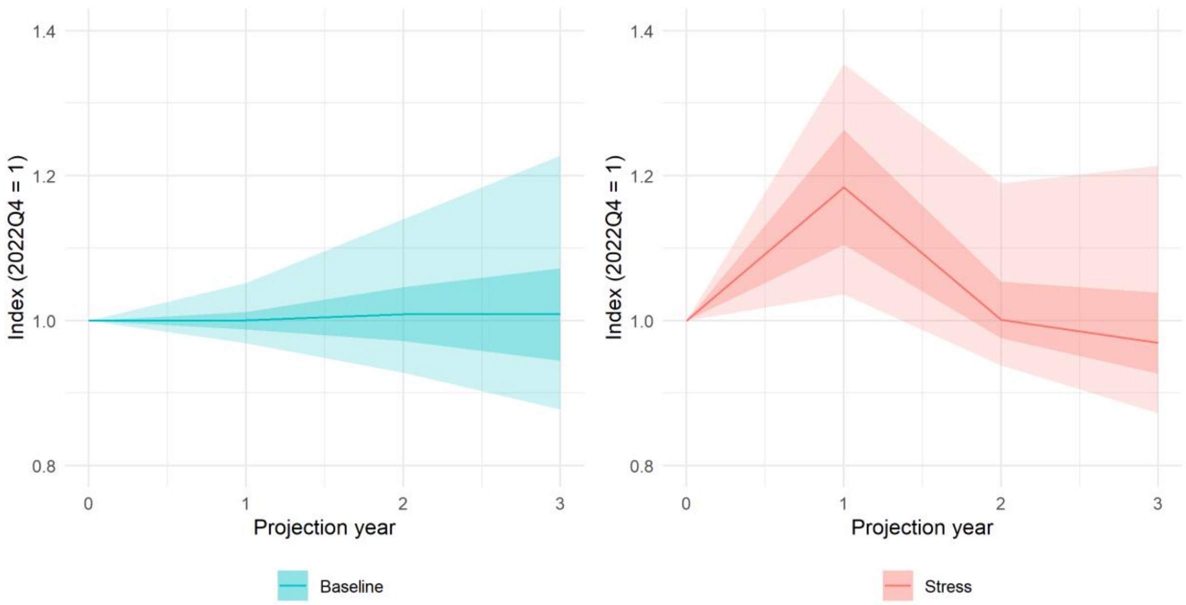
Climate risks can be transmitted heterogeneously across firms and banks. Sectors with high fossil fuel needs, which are reflected in high emissions of environmentally harmful greenhouse gases, may tend to prove more vulnerable. At the same time, the risks for individual firms within the same sector might be lower than for others. In particular, technological adaptation may be more advanced at some firms, as reflected in a lower emissions intensity. Figure 7 documents the high level of heterogeneity in terms of the impact on individual firms' PDs for the NGFS scenarios. In the stress scenario (right-hand chart), the differences in the increase in PD between the firm in the 10th percentile and that in the 90th percentile amount to almost 50 percentage points after 3 years. While the "median" firm experiences an increase of just under 20%, the PD of the firm in the 90th percentile rises by almost 50% as compared with the starting value. Heterogeneity is somewhat lower by comparison for the alternative short-term scenario (STS, Figure 8), but the dispersion between firms is nevertheless substantial.

Figure 7: Distribution of projected PD estimates across firms – NGFS



Notes: The figure depicts the projected quantiles of firm-level PDs (for the median values across variants of the micro model) for the scenarios of the NGFS (Network for Greening the Financial System). PDs are expressed as multipliers with respect to the starting point. The solid line represents the median, the dark shaded area represents 25-75th percentiles, and the light shaded area shows 10-90th percentiles.

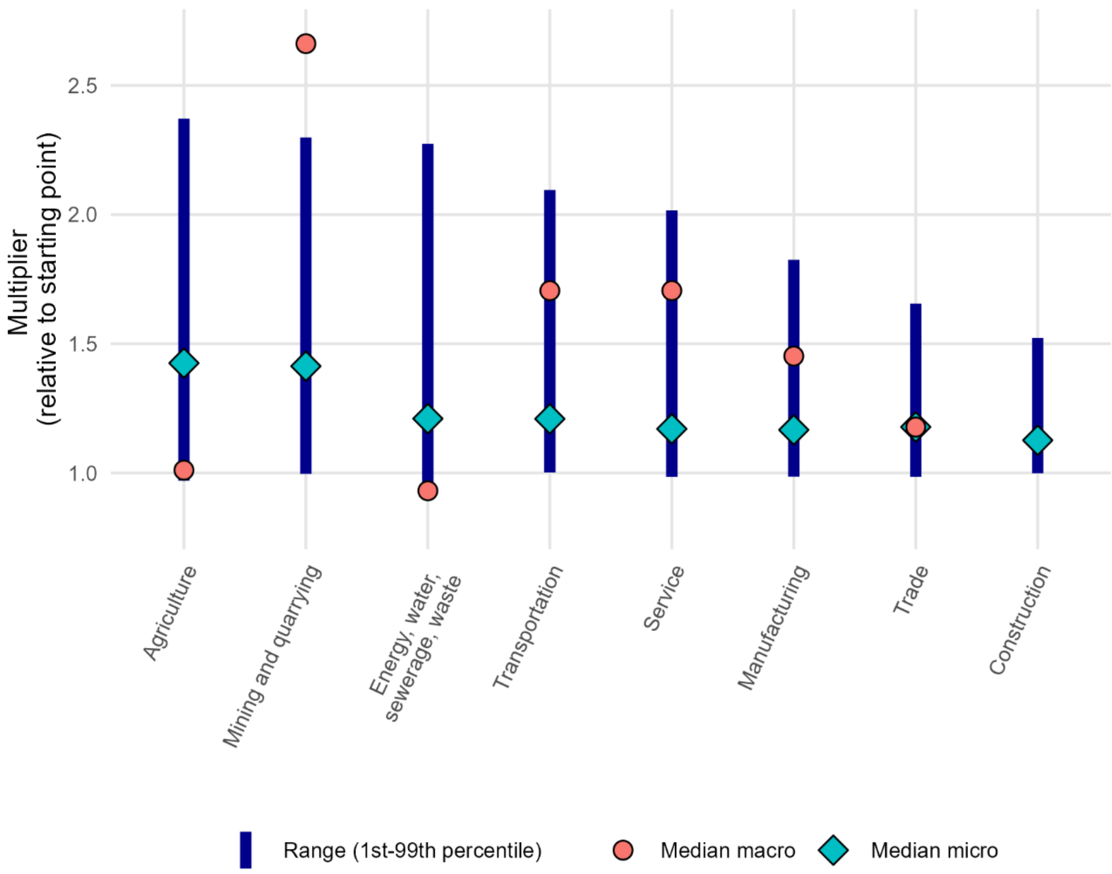
Figure 8: Distribution of projected PD estimates across firms – STS



Notes: The figure depicts the projected quantiles of firm-level PDs (median across variants of the micro model) for the Short Term Scenarios (STS). PDs are expressed as multipliers with respect to the starting point. The solid line represents the median, the dark shaded area represents 25-75th percentiles, and the light shaded area shows 10-90th percentiles.

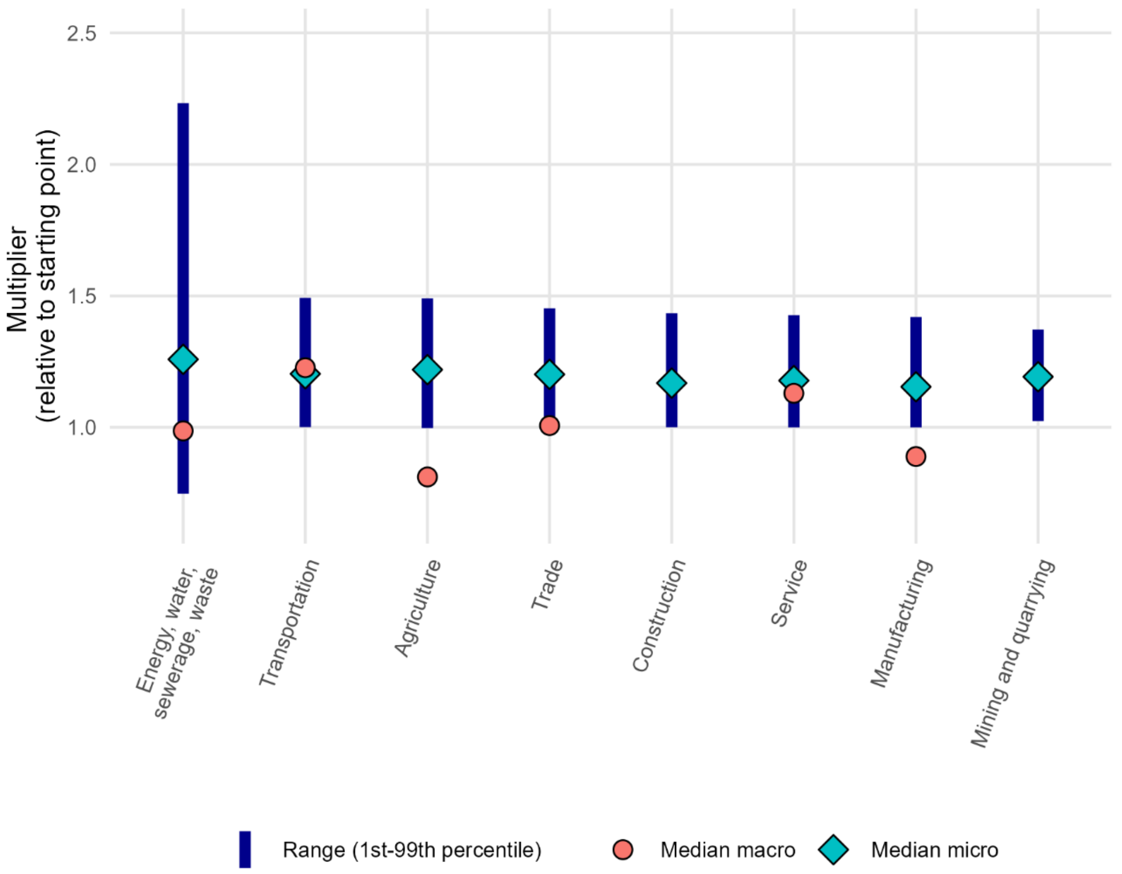
Pronounced differences in how much firms are impacted by transition risks are also evident when looking at the stress test results at the level of individual economic sectors (Figure 9 and Figure 10). In the NGFS stress scenario (Figure 9), in particular, it is clear when looking at the micro model that emissions-intensive sectors (e.g. agriculture, energy, transport) are more affected by PD increases in the median. At the same time, the dispersion between firms is more pronounced in the emissions-intensive sectors. In the energy sector, for example, some firms see their PDs more than double. These are firms that are heavily dependent on fossil fuels. It is worth noting that a small proportion of firms actually have lower PDs in the stress scenario (i.e. multipliers smaller than 1). These are firms whose business model is already largely based on renewable forms of energy. For the alternative scenario (STS, Figure 10), there is also heterogeneity between sectors, but this is less pronounced than in the NGFS scenario.

Figure 9: Estimated PDs across economic sectors (stress-baseline difference in NGFS scenarios)



Notes: The figure depicts the projected PDs (difference between stress and baseline relative to starting point) for corporate borrowers across different economic sectors in year 3 of the NGFS scenarios. In addition to median estimates for the micro and macro model, respectively, the figure also presents the within-sector range of firm-level PD estimates from the micro model. Macro estimates for the median of the construction sector are not depicted to ease readability.

Figure 10: Estimated PDs across economic sectors (stress-baseline difference in STS scenarios)



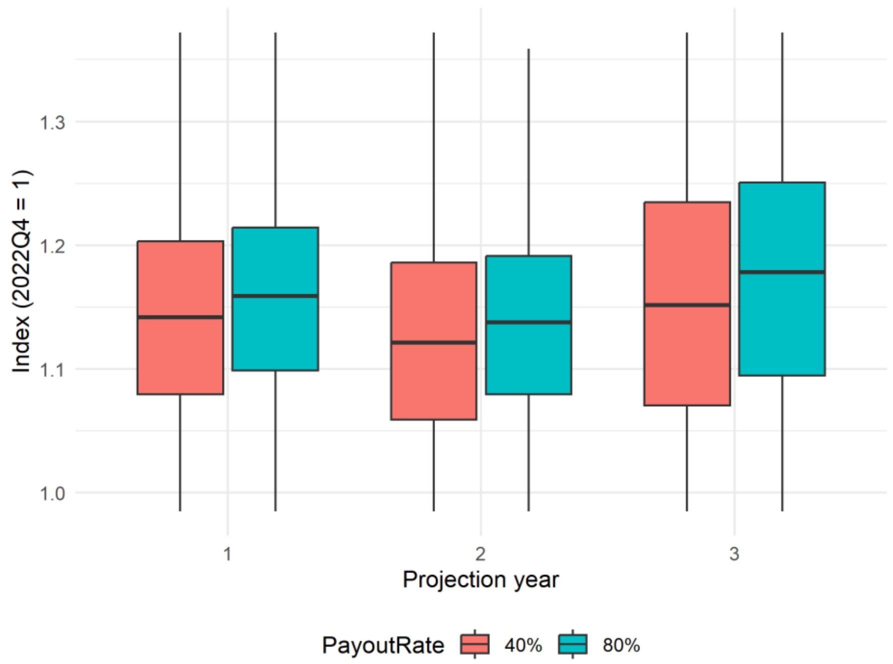
Notes: The figure depicts the projected PDs (difference between stress and baseline relative to starting point) for corporate borrowers across different economic sectors in year 1 of the STS scenarios. In addition to median estimates for the micro and macro model, respectively, the figure also presents the within-sector range of firm-level PD estimates from the micro model. Macro estimates for the median of the sectors construction, and mining and quarrying are not depicted to ease readability.

4.3 Sensitivity

4.3.1 Micro-level approach

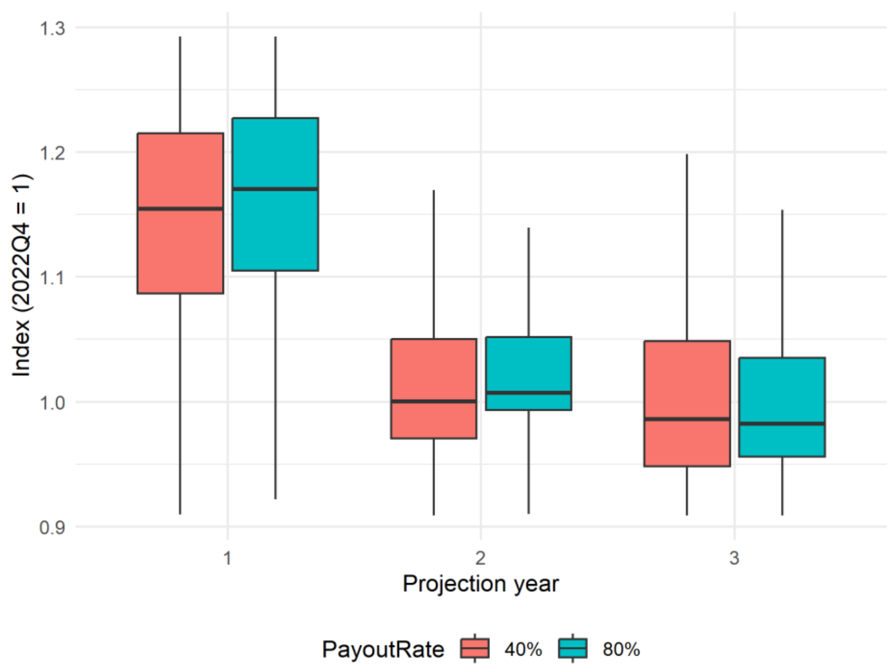
Figure 11 and Figure 12 show the impact of the assumptions regarding firms' payout rates (variants B1 and B2; see Section 3.1.3) on the projected development of PDs. Higher assumed payout rates are also associated with higher increases in PDs. This is because payouts withdraw liquidity from firms that is then no longer available to reduce debt or build up liquidity buffers. A higher debt ratio and a lower liquidity ratio both impact negatively on PDs. As there is uncertainty about firms' actual payout rates, both variants are taken into account in the results in Sections 4.1 and 4.3. It is important to note, though, that differences in projected PD paths seem contained, i.e. assumptions taken on payout rates do not drive our results.

Figure 11: Impact of firms' modelled payout rate on PDs (NGFS stress)



Notes: The figure depicts the projected quantiles of firm-level PDs (median, 25-75th percentiles, 10-90th percentiles across variants of the micro model), where variants are divided with respect to the assumed payout rate of firms (40% vs. 80%). PDs are expressed as multipliers with respect to the starting point.

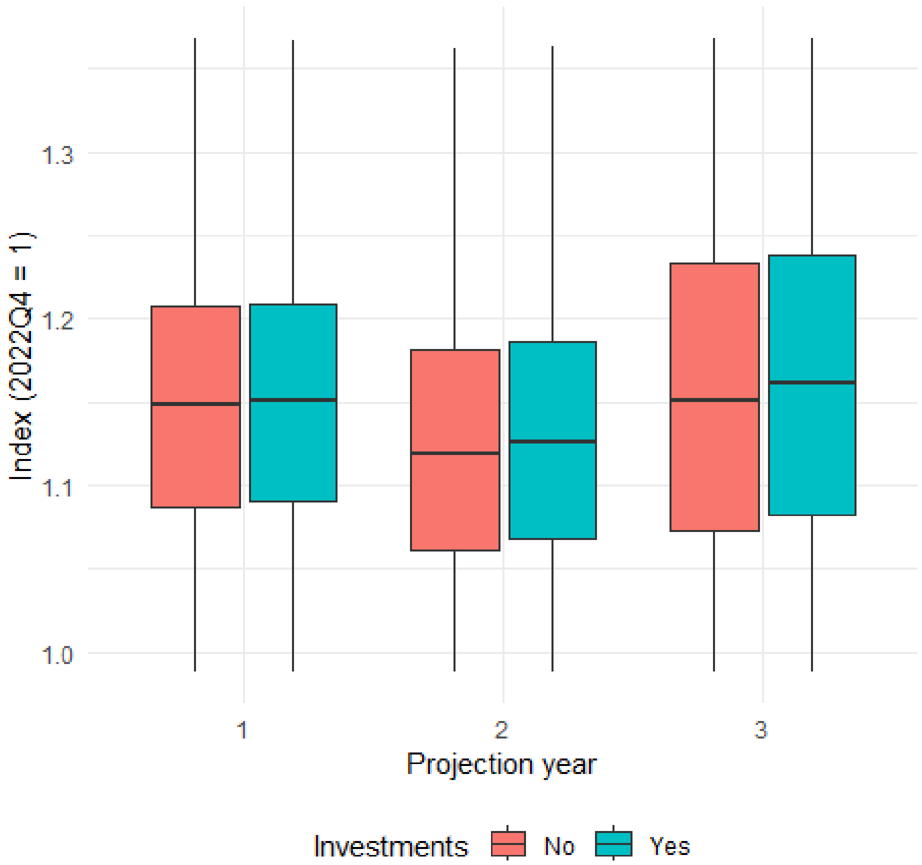
Figure 12: Impact of firms' modelled payout rate on PDs (STS stress)



Notes: The figure depicts the projected quantiles of firm-level PDs (median, 25-75th percentiles, 10-90th percentiles across variants of the micro model), where variants are divided with respect to the assumed payout rate of firms (40% vs. 80%). PDs are expressed as multipliers with respect to the starting point.

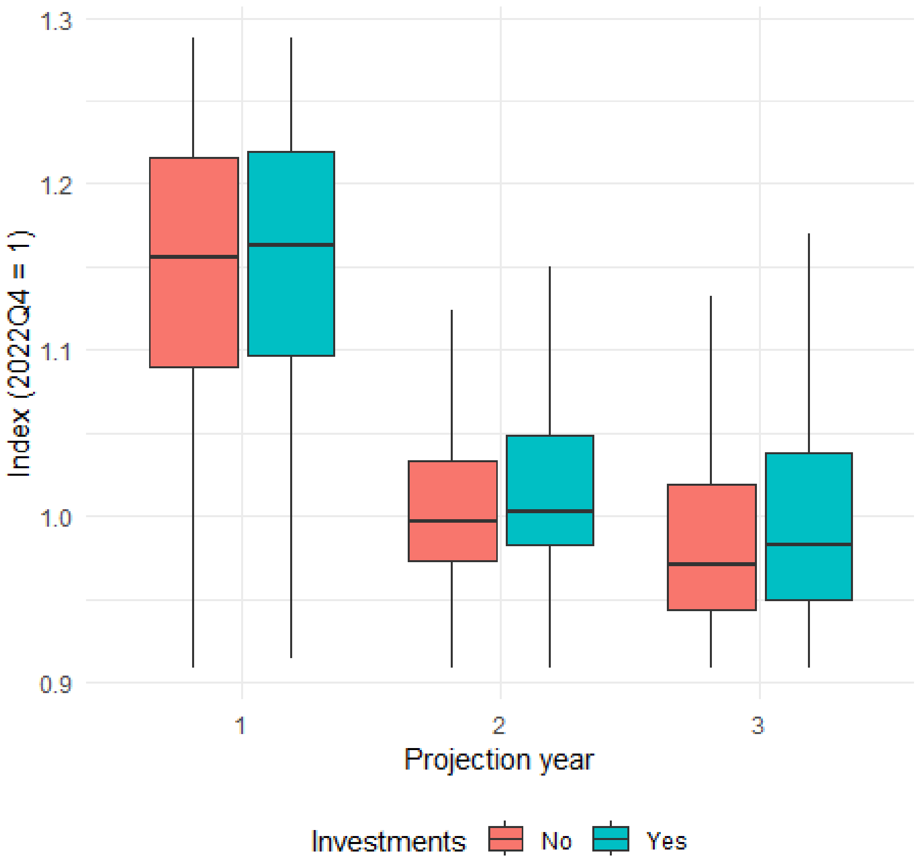
Figure 13 and Figure 14 show that the assumptions about additional climate investment by firms, too, impact adversely on the projected PD developments. Under the NGFS and STS stress scenarios, additional climate investment is assumed to be financed by firms by taking on more debt (see Section 3.1.3). Their interest expenses thus increase over time. Higher debt ratios and higher interest expense ratios both have an adverse impact on PD developments. In the STS stress scenario, firms' climate-related new debt drives PDs more strongly than in the NGFS scenario; this is because investments are made within a relatively small timeframe and are therefore higher. Still, assumptions taken on additional climate investments are not a predominant driver of projected PD paths. Note that the results presented in Sections 4.1 and 4.3 are always based on the assumption that climate investments are made. This reflects the fact that, without investment, carbon emissions cannot be reduced in line with the scenario pathways, either.

Figure 13: Impact of firms' modelled climate investments on PDs (NGFS stress)



Notes: The figure depicts the projected quantiles of firm-level PDs (median, 25-75th percentiles, 10-90th percentiles across variants of the micro model), where variants are divided into variants where climate investments are modelled (Investments = YES) vs. variants where climate investments are not modelled (Investments = NO). Only variants where climate investments are modelled are included in the other analyses of this paper; variants where climate investments are not modelled are excluded in the remainder of this paper. PDs are expressed as multipliers with respect to the starting point.

Figure 14: Impact of firms' modelled climate investments on PDs (STS stress)



Notes: The figure depicts the projected quantiles of firm-level PDs (median, 25-75th percentiles, 10-90th percentiles across variants of the micro model), where variants are divided into variants where climate investments are modelled (Investments = YES) vs. variants where climate investments are not modelled (Investments = NO). Only variants where climate investments are modelled are included in the other analyses of this paper; variants where climate investments are not modelled are excluded in the remainder of this paper. PDs are expressed as multipliers with respect to the starting point.

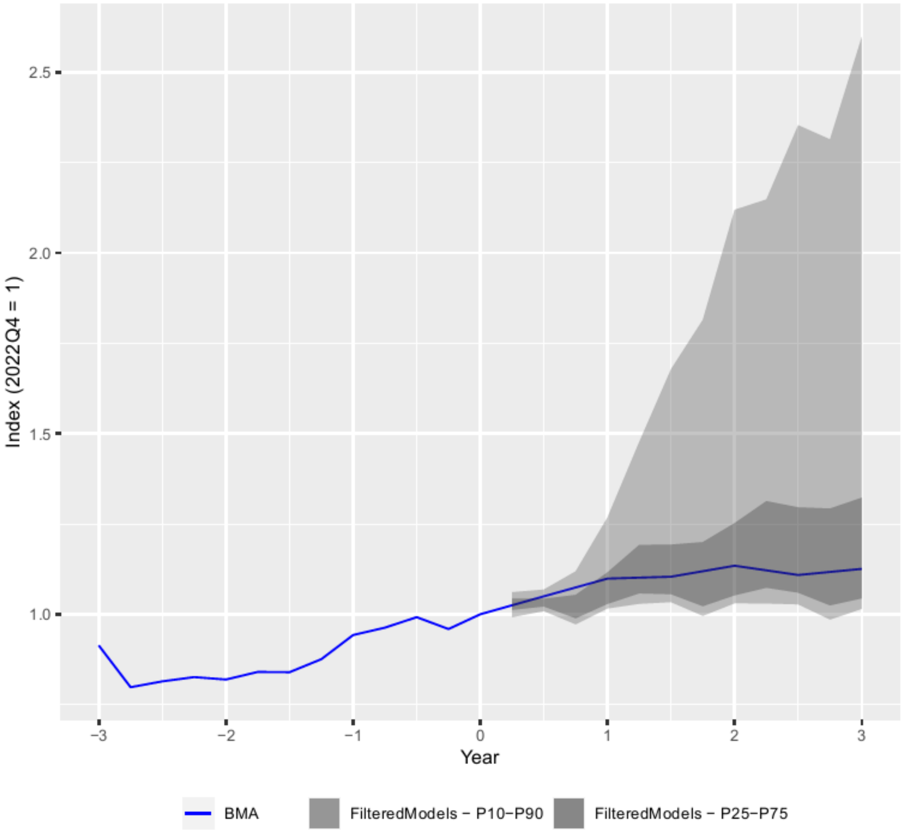
4.3.2 Macro-level approach

The path generator approach already addresses model uncertainties to a large extent through the model filtering process and the subsequent merging of the surviving models via BMA. In the first step of the approach, the unfiltered model space is filtered using the criteria listed in Section 3.2.1. In this context, the PD projections from the models of the filtered model space already show, for a large percentage of economic sectors, a variance that is more than 80% lower than for the unfiltered model space.

In the second step, the BMA procedure ensures that the PD projections of the models from the filtered model space are aggregated to form one weighted projection. To help the reader visualise this process, Figure 15 provides a graphical representation of the projection range of

PDs from the filtered model space and the PD weighted using BMA based on the example of the adverse NGFS scenario. The light and dark grey areas represent the ranges between the 10th and 90th percentiles and between the 25th and 75th percentiles. The weighted PD, indicated by the blue line, is predominantly between the 25th and 75th percentiles of the filtered model space over the three-year projection horizon. During the first year of the projection, it is occasionally above the 75th percentile. One particular indicator of how different the projections of individual models can be is visible in the gap between the 75th and 90th percentiles. The model in the top decile in the third year of the projection predicts a 150% increase in PD (indexed to an initial value of 1). The corresponding model in the 75th percentile, on the other hand, projects a roughly 30% increase.

Figure 15: Projections from filtered models and BMA aggregation



Notes: The figure depicts the historical aggregate PD for corporate loans (weighted by exposure) as well as the projected PDs (both expressed as multipliers with respect to the last observed quarter in t=0) for 144 filtered models over the three-year stress test horizon for the NGFS stress scenario. Up to and including the last observed quarter, the blue line depicts the historical PD. Starting with the first projected quarter, the blue line depicts the projected PD obtained by applying Bayesian model averaging to all filtered models. The dark shaded area depicts the range between P25 and P75 in the filtered model space. The light shaded area depicts the range between P10 and P90 in the filtered model space.

Since BMA weighting is based on the out-of-sample performance of the individual models, it is possible for individual models to be assigned a very high weight and thus be major drivers of the projection. That is why we also look at the distribution of weights by economic sector. For this purpose, we calculated the Gini coefficient, which by definition is between 0 (perfect equality) and 1 (maximum inequality). The Gini coefficient is uniformly distributed between 0.25 and 0.58 across all economic sectors, which implies only limited concentration of weights for most economic sectors.

4.4 Scenario-dependent expected and realised credit losses

In supervisory stress tests, it is usually the reduction in banks' common equity tier 1 capital ratio (CET1 depletion) that is reported as a key metric. To calculate this metric, we need, amongst other things, reliable information on the (future) risk-weighted assets that correspond to the respective loans to firms. As this information is not available for the corporate loan portfolios, the financial impact associated with the materialisation of transition risks for banks in the NGFS scenario is classified on the basis of two alternative metrics. These are, first, the (ex ante) risk provisioning to be established in the form of the expected losses for the year and, second, the (ex post) required additional credit losses (ACLs) on a loan-by-loan basis. [34]
Risk provisioning is determined on the basis of PD, LGD and credit volume.[35] The additional credit losses on a loan-by-loan basis are calculated using a Monte Carlo simulation, in which the occurrence of "real" credit defaults and the associated losses are simulated over the three-year projection period for 1,000 different runs and netted against the risk provisions established up to the time of default. This approach can be used to illustrate the paths[36] that form the margin of the distribution of losses, which are particularly disadvantageous to banks. These (hypothetical) paths are particularly critical for banks, as the required credit losses on credit portfolios go well beyond the ex ante provisions. Both indicators, i.e. both the ex ante risk provisioning and the specific credit losses observed ex post, are reported for both the micro and macro approach and are also differentiated by bank size (less significant institutions (LSIs) or significant institutions (SIs)).[37] The scenario-dependent results represent the difference between the stress and baseline scenarios and thus the additional risk provisioning that goes beyond what is already necessary in the baseline scenario.

[34] Due to the methodological approach used in this stress test, the nomenclature used here differs slightly from the usual definitions according to the German Commercial Code (*Handelsgesetzbuch*). In addition, loans are not classified according to the logic of IFRS 9, which would require additional data on the precise cash flow structures and the maturities of the loans granted. The term "risk provisioning" represents the sum of the annual credit losses expected a priori on a loan-by-loan basis rather than at the general portfolio level. This peculiarity is due to the fact that this stress test does not involve clustered loan portfolios; instead, changes in PD/LGD always relate to a specific loan. By contrast, the term "specific credit loss" refers to the "realised" additional losses at the end of the stress horizon that are not already covered by the risk provisioning that has been established. The formulas for calculating the parameters are listed in Appendix B.

[35] The calculation logic for LGDs is explained in Appendix B.

[36] It is specifically the 90th and 99th percentiles of the distribution which are reported.

[37] Of the roughly €2,084 billion in domestic loans to firms, approximately €1,140 billion (54.7%) is attributable to significant institutions and, accordingly, €944 billion (45.3%) to less significant (small and medium-sized) institutions. The latter consist mainly of cooperative banks and savings banks whose scope of operation is predominantly regional.

The aggregate results for banks' scenario-dependent additional risk provisioning can be found in Table 4.[38] The table shows that, on aggregate, the losses incurred in the banking system are moderate. Cumulated over three years, around 0.23% of the corporate loan volume would have to be written down in the macro approach. Using the micro approach, too, additional losses would be manageable, at 0.29%. At the same time, a comparison of the two approaches reveals differing dynamics. Whilst in the macro approach, the bulk of the additional losses are already incurred in the first year of observation (0.17%), credit losses in the micro approach are distributed more evenly over time, reaching a peak (0.11%) at the end of the analysis period. There are also differences between the two approaches when the banks are sorted by significance. Although both modelling approaches indicate that significant institutions (SIs) experience higher cumulative losses than less significant institutions (LSIs), the difference between the two groups of banks is much greater when using the macro approach, at roughly 0.11 pp (SIs: 0.29% vs LSIs: 0.18%). Using the micro approach, it amounts to only around 0.04 pp (SIs: 0.31% vs LSIs: 0.27%).

Table 4: Additional required risk provisioning (in % of loan volume, difference between NGFS stress and baseline scenarios)

	Aggregate		SIs		LSIs	
	Macro	Micro	Macro	Micro	Macro	Micro
Year 1	**0.166**	0.095	**0.185**	0.100	**0.148**	0.089
Year 2	0.011	0.089	0.017	0.093	0.005	0.085
Year 3	0.056	**0.108**	0.085	**0.119**	0.030	**0.099**
Cumulated	0.233	0.293	0.288	0.313	0.183	0.273

Notes: For the micro approach, expected credit losses in the median variant are depicted. SIs: Significant Institutions; LSIs: Less Significant Institutions.

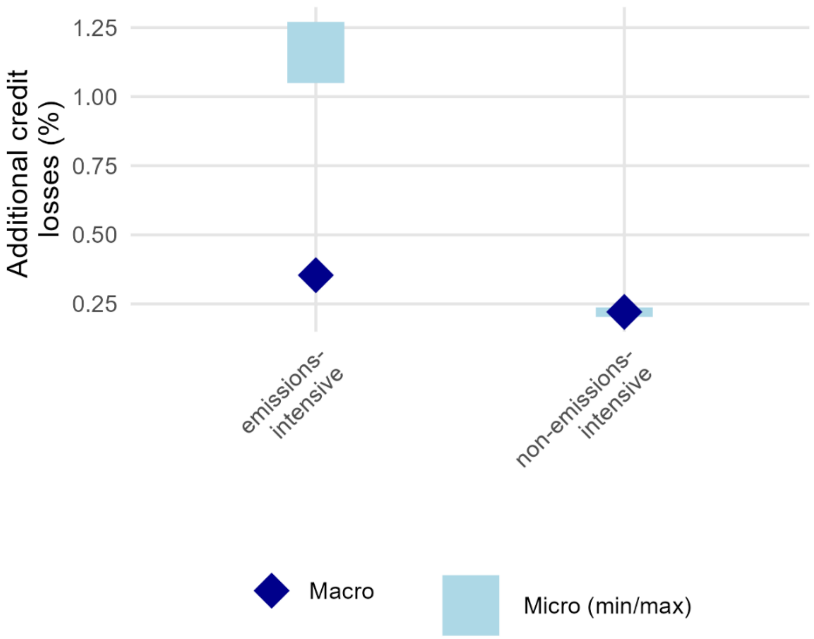
With regard to the share of lending in particularly emissions-intensive economic sectors,[39] the two bank aggregates barely differ. The share of loans to these sectors amounts to around 10.3% for the SIs and approximately 9.6% for the LSIs. This differentiation by emissions intensity has a considerable influence on the additional risk provisioning that needs to be built up by

[38] Credit losses would be around 20-25% higher if the severest variant for each bank is used. All banks as an aggregate would then require cumulative risk provisioning of 0.360 pp, as opposed to 0.293 pp in the median variant. This figure would increase from 0.313 pp to 0.383 pp for the SIs and from 0.273 pp to 0.341 pp for the LSIs.

[39] Those economic sectors that participate in the EU Emissions Trading System are deemed to be emissions-intensive. The individual economic sectors that fall under this classification are listed in Appendix A3.

banks over the three-year horizon. When the macro approach is applied, the provisioning to be built up by the more emissions-intensive sectors is, on average, 1.6 times higher than that of the less emissions-intensive sectors (0.35% vs 0.22%; see Figure 16). This ratio becomes even more significant when the micro approach is applied. Depending on the modelling variant used, the estimated values are between 4.8 and 5.6 times greater for loans within the more emissions-intensive economic sectors. Meanwhile, there is barely any variation between the results of the eight different modelling variants for the less emissions-intensive sectors (minimum: 0.20%; maximum: 0.24%). In the more emissions-intensive sectors, by contrast, not only is the level of required credit losses considerably higher, but the range of results is also somewhat wider (minimum: 1.05%; maximum: 1.27%).

Figure 16: Additional losses in the NGFS scenario by emissions intensity of borrowers



The (cumulative) credit losses exceeding the risk provisioning established a priori at the end of the final projection year can be seen in Table 5, showing that where an unfavourable pathway materialises (in one out of ten cases or one out of one hundred cases), much more extensive losses would be expected in the corporate loan portfolio. Here, the additional credit losses are aggregated using the 90th and 99th percentile values for all banks, for SIs and LSIs (aggregation weighted by credit volume in each case) as well as for a "fictitious overall bank" (FOB), which accounts for all corporate loans and thus represents the German banking sector in its entirety. Each of the aggregate values are differentiated by the micro and macro approaches.

Table 5: Additional credit losses (ex post), in % of loan volume

	Aggregate		SIs		LSIs		FOB	
	Macro	Micro	Macro	Micro	Macro	Micro	Macro	Micro
90th percentile	0.529	0.291	0.496	0.230	0.570	0.365	0.232	0.170
99th percentile	1.291	0.770	1.064	0.580	1.566	1.001	0.294	0.187

Notes: For the micro approach, specific credit losses in the median variant are depicted. SIs: Significant Institutions; LSIs: Less Significant Institutions; FOB: Fictitious overall bank, that accounts for all corporate loans and thus represents the German banking sector in its entirety.

For the real defaulted loans of the 99th percentile (90th percentile) aggregated across all banks, around 1.29% (0.53%) of the credit volume still has to be written down in addition to the existing risk provisioning in the macro approach, and 0.77% (0.29%) in the micro approach.[40] At the same time, viewed from this perspective, the bulk of the impact shifts from the SIs towards the LSIs. On account of the typically low number of credit relationships and the resulting limited diversification among very small banks, the unfavourable margin of the bank distribution shows especially high values here (macro approach: 1.57% (0.57%); micro approach: 1.00% (0.37%)).[41] In that regard, it is precisely the less diversified banks and those that have granted a large volume of loans to firms or economic sectors especially exposed to transition risks that have a heightened risk potential.

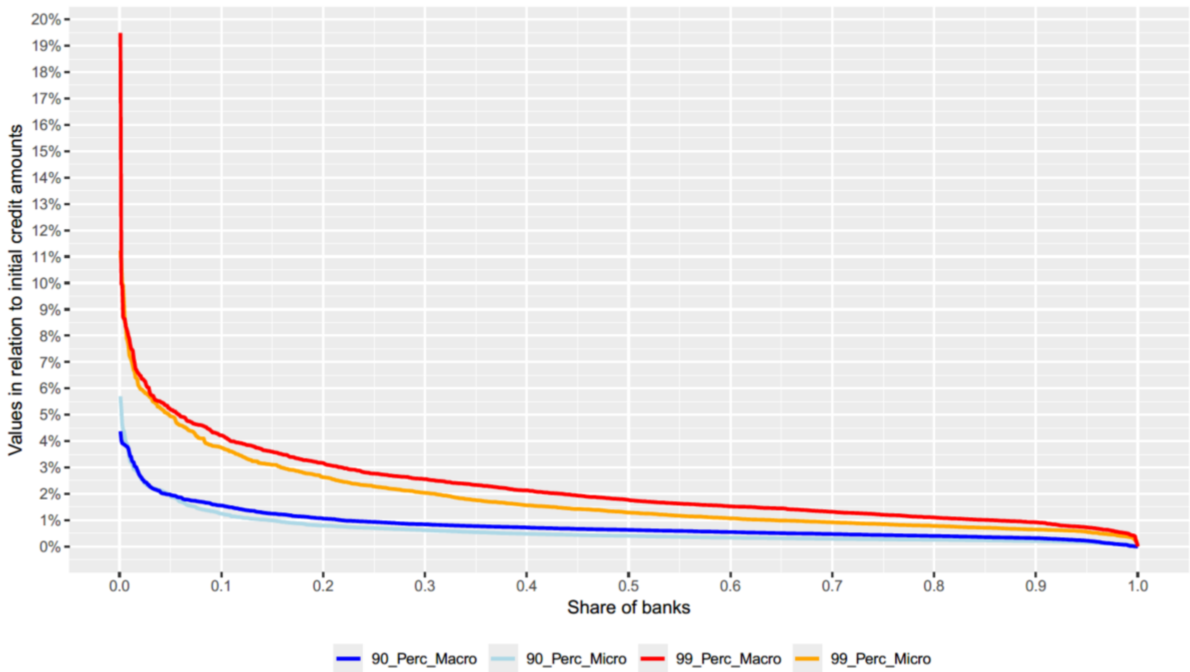
In addition, the results exhibit a significant difference between the weighted aggregate values of the 90th and 99th percentiles of all banks and the 90th and 99th percentiles of the "aggregate bank", which incorporates all corporate loans. The difference between these two metrics is because in the case of the aggregate bank, there are considerably more pronounced diversification effects between all of the (independent) individual loans than when only the 90th and 99th percentile values are weighted. Exclusively marginal and extreme values taken from the individual bank portfolios are used and weighted by the credit volume of the respective bank here. This is consistent with the assumption that all of the banks' corporate loan portfolios suffer a strong or very strong shock at the same time. Ultimately, both approaches are marginal assumptions. The assumption of perfectly synchronised co-movement between banks' portfolios will likely tend to overestimate the risk potential for the banking sector as a whole; conversely, the assumption of complete independence is expected

[40] Here, it should be noted that due to the typical assumption of a static balance sheet in stress tests as well as the lack of data on loan maturities during the observation period, no loans can, or do, reach maturity, by definition. This means that risk provisioning built up ex ante but no longer required for fully repaid loans is accordingly not released either, and cannot be offset against any losses incurred during this period. However, as this methodological restriction affects both the baseline and stress scenarios, and the analysis period is fairly short, at three years, it is likely that the required additional credit losses will only be slightly overstated.

[41] Banks with 15 or fewer credit relationships were classified as outliers and excluded from the analysis.

to make the result appear too positive, as the pronounced heterogeneity of the German banking sector is not considered and the disproportionately strong impact on individual institutions is therefore "smoothed out".

Figure 17: Distribution of additional credit losses across the sample of banks



Notes: The figure depicts the results of a Monte Carlo simulation with 1,000 runs. The additional credit losses are calculated as differences between the actual credit losses and the specific risk provisions established up to that point. Banks with 15 or fewer credit relationships were classified as outliers and excluded from the sample. The graphs show banks' additional burdens in descending order. Red (macro) and orange (micro) represent the 99th percentile, blue (macro) and light blue (micro) represent the 90th percentile of the distribution.

Figure 17, which depicts the required additional credit losses at the individual bank level in descending order, reinforces this assertion. The chart shows that losses are not evenly distributed across the banks; rather, a small portion of these banks are severely affected. In both modelling approaches, approximately 5.0% of banks record a value of around 5.0% (2.0%) or higher at the 99th (90th) percentile,[42] whilst one-half of banks have an additional loss of only 1.8% (0.6%) at most in the macro approach and 1.3% (0.4%) in the micro approach, even assuming very unfavourable developments.[43]

[42] The figures for the respective percentiles are based on a simulation in which the actual defaults over the three-year horizon are calculated for each individual loan agreement in 1,000 runs. The individually projected probabilities of default come into play here. The real credit losses incurred in corporate loan portfolios at the end of the third year can thus be calculated for each bank. To work out the potential additional loss, the expected credit losses established a priori must be deducted from the result. High percentiles are purposely chosen to illustrate the possible loss potential. For instance, the 99th percentile reflects the ten worst (i.e. lowest) loan portfolio values of the 1,000 runs and thus a rare extreme scenario. In that regard, the respective value for the highest percentile should be interpreted as a theoretical upper bound rather than a reference value for economically prudent risk provisioning on the part of banks.

[43] If the least favourable condition for each respective bank were to be used in the micro approach rather than the median variant, the specific credit loss requirement would almost double. The hardest-hit 5% of banks would thus have to write down in excess of an additional 9.4 pp (3.7 pp) and one-half of institutions at least 2.7 pp (1.1 pp).

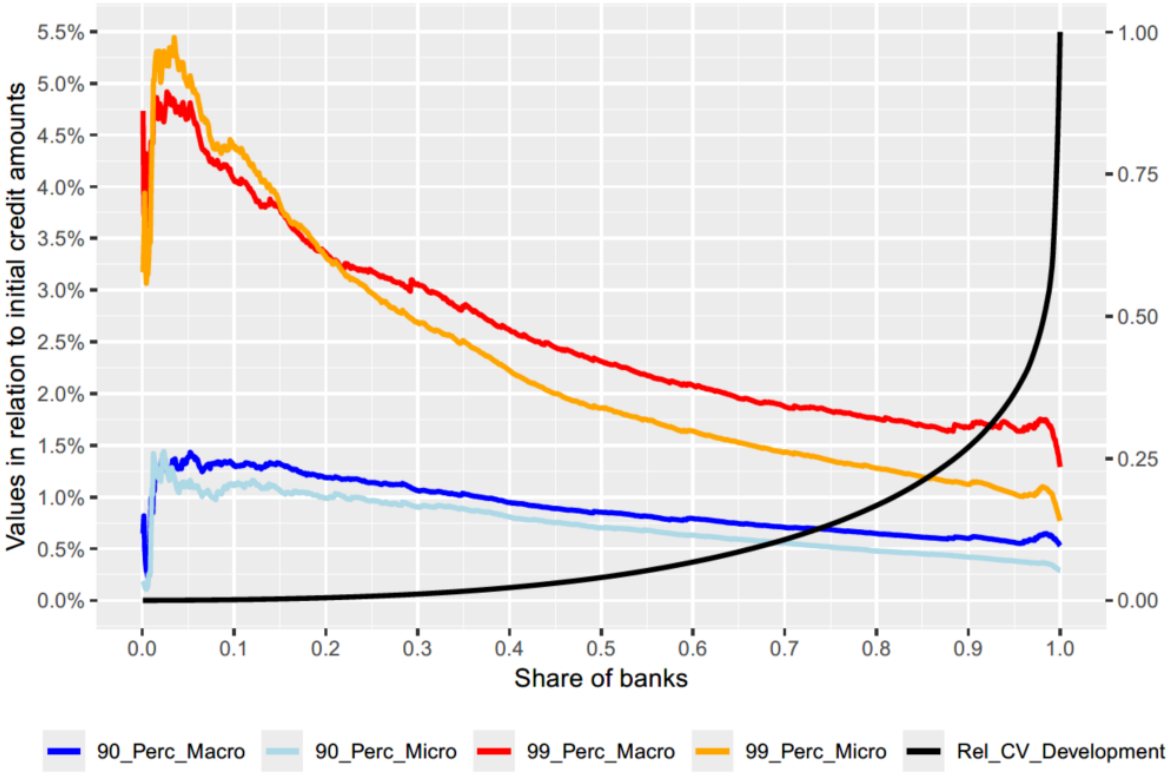
Figure 18 provides an overview of the relationship between relative additional credit losses and bank size, which is defined by the respective total volume of loans granted. The chart plots the moving average of the share of additional credit losses in relation to banks' credit volumes for the 90th and 99th percentiles, for both the micro and macro approaches. In addition, the black line shows the distribution of the credit volume in the banking sector, which is clearly concentrated on the largest banks (Gini coefficient: 0.81).[44] The gap between the 90th and 99th percentiles is clearly pronounced even when including the credit volume. This applies to both the micro and macro approaches. The decline in relative additional credit losses when credit volumes rise indicates that smaller credit institutions are disproportionately affected by heightened stress in comparison to larger banks. This is illustrated, in particular, by the marked decline in relative additional credit losses for the largest banks at the far right-hand side of the chart, which is attributable to both their high share of credit volume and comparatively lower credit losses. Despite this decline, the relative gap between the 99th percentile and the 90th percentile remains pronounced throughout. The 99th percentile values, for example, equal at least 2.5 times (macro approach) or 2.4 times (micro approach) the respective values for the 90th percentile across all observations.[45] The more marked differential between the 99th and the 90th percentile values indicates that, in extreme stress events, relative additional credit losses decrease comparatively strongly in line with the size of the loan portfolio. For smaller institutions, in particular, an increase in the stress level thus has an especially negative impact on the required additional credit losses.

Furthermore, it is worth noting that the 99th percentile in the micro approach declines more strongly than the 99th percentile in the macro approach, while the 90th percentiles decrease relatively evenly in both approaches. At the same time, when observing the 99th percentile, the smallest institutions (approximately 20%) are more affected in the micro approach than in the macro approach. This is likely due to the fact that PD development is modelled at the granular firm level in the micro approach, while in the macro approach it is projected at the sector level. The intrasectoral heterogeneity of PD development thus creates an additional dimension, which tends to increase the variance in the credit loss result and, above all, causes the tails of the distributions of small and thus less diversified portfolios to rise. In summary, it can be maintained that the additional credit losses attributable to transition risks tend to decrease in line with the institution's significance for the banking sector, suggesting that the transition risks for the German banking system as a whole are likely to be manageable.

[44] The number of loans granted to firms is somewhat less concentrated on the largest banks (Gini coefficient of 0.61).

[45] Adjusted for outliers, the ratio of the 99th and 90th percentiles on the left tail is around 5.0 for the micro approach and around 3.7 for the macro approach.

Figure 18: Distribution of additional loan losses depending on total assets



Notes: The figure depicts the results of a Monte Carlo simulation with 1,000 runs. The additional credit losses are calculated as differences between the actual credit losses and the specific risk provisions established up to that point. Banks with 15 or fewer credit relationships were classified as outliers and excluded from the sample. The graphs show banks' additional burdens as a moving average on the banks' credit volume. Red (macro) and orange (micro) represent the 99th percentile, blue (macro) and light blue (micro) represent the 90th percentile of the distribution. The black line shows the distribution of the credit volume in the banking sector and is plotted on the right y-axis.

5 Conclusion

New modelling approaches are required in order to assess financial risks associated with climate change using stress tests. Traditional top-down stress test models are not able to adequately depict the heterogeneity in institutions' vulnerability to transition risks. We propose a targeted, multi-layered analytical framework that takes into account the heterogeneity of risks across economic sectors and firms. Our stress test uses two independent modelling approaches, a micro and a macro model, to translate the scenarios into credit risk parameters. The macro approach derives developments in probabilities of default at sector level, thus taking into account differences between the sectors. The micro approach additionally reflects differences in how individual firms are impacted. For our analysis, we use a large sample of German banks (~1,300) of different sizes and business models. All in all, our model framework allows granular quantification of risks whilst at the same time taking into account model uncertainty through benchmarking of modelling approaches and by presenting a range of possible results.

For a scenario that envisages an orderly transition to net zero emissions by 2050 (NGFS scenario), our results show an average increase of up to 40% in the probabilities of default for non-financial corporations after three years. In an alternative scenario assuming an abrupt increase in the carbon price to €200 (STS scenario), the probabilities of default rise to a similar extent. In the micro approach, there is an aggregate increase in probabilities of default of up to 30% in the short term, but over the three-year horizon the falling interest rates and recovering equity prices[46] under the STS scenario result in less adverse PD projections. In principle, there is a great deal of heterogeneity between firms from different economic sectors: PDs increase more strongly in the agriculture, utilities and transport sectors, for example, and the impact on credit risk also differs between firms in the same economic sector. Whilst significantly stronger increases in PDs emerge for emissions-intensive firms, credit risk is not as high for firms with low emissions. In the NGFS scenario, relative to credit volume, the cumulative credit losses as a result of mounting credit risk over the observation horizon are between around 0.23% (in the macro approach) and 0.36% (the most adverse variant observed at the firm level in the micro approach). These are always additional losses that would place extra strain on banks during possible economic or financial crises. Furthermore, individual banks may well be much worse affected than the aggregate due to the composition of their loan portfolio.

Broadly, results point into the same direction when comparing the micro model and the macro model. This is reassuring given the relative novelty of the modelled risk and underlines the importance of benchmarking both models. Still, it is important to highlight that our framework produces noteworthy differences in results across models, emphasizing the key role of model design in stress testing. More specifically, results differ across models in two aspects: First, a short-term shock as depicted in the STS scenario affects PDs instantly in the micro model and only with a slight delay in the macro model. This can be attributed to modelling choices in the bridge equations, where changes in macro variables are translated into firms' balance sheets more directly. Second, the magnitude of additional credit losses is higher for emission-intensive borrowers in the micro model compared to the macro model. Potentially, linear elasticities of sectoral PDs with respect to past carbon prices in the macro model underestimate the impact of higher-than-hitherto-observed carbon price increases, whereas bridge equations used in the micro model allow to abstract from historical elasticities.

[46] With the use of a DSGE model, a different methodology is applied to generate the STS scenario than that used to generate the NGFS scenario. This means that underlying assumptions about scenario variables such as interest rates and equity prices, and thus also the resulting scenario pathways, may differ significantly.

Although our analytical framework provides important and targeted insights into the quantification of climate risks, it is subject to certain constraints, largely owing to insufficient data. In particular, only very limited data on carbon intensity at the firm level are available, which means that approximations (e.g. sector averages) had to be used in many instances. New disclosure requirements relating to sustainability, such as the EU Corporate Sustainability Reporting Directive (CSRD), are expected to improve the data situation over the medium term. Physical risks from climate change were deliberately not integrated into our stress test. There are two key factors at play here. First, current climate policy decisions only impact the speed of climate change after a considerable time lag. This necessitates long-term modelling, which is incompatible with the nature of a bank stress test with static balance sheets. Second, limited data availability on physical risks also places major constraints on climate risk modelling. Physical risks typically materialise regionally, requiring granular data on risks posed by certain weather events and specific knowledge about the location of borrowers' business activities and collateral. While our analysis focuses exclusively on corporate credit risk, substantial vulnerabilities may arise for banks via the market risk channel. Future extensions to our modelling framework may integrate the effects of financial investors' reassessment of climate risks on banks' balance sheets, e.g. through the materialization of stranded assets.

Our results have a number of implications for microprudential and macroprudential supervisors. Climate risks are an important risk category for banks that drive the conventional risks (e.g. credit risk, market risk, etc.). The regular use of dedicated climate risk stress tests allows to gauge the overall risk potential for individual banks and the whole system at a given point in time. While our paper, like most supervisory climate stress tests conducted so far, looks at the effects of climate risks in isolation, there may be possible interactions in the financial system between climate risks, other macroeconomic shocks and general financial vulnerabilities. As was shown in the recent European "Fit-for-55" climate scenario analysis, these interactions may give rise to severe amplification effects, which could lead to otherwise manageable climate risks becoming a threat to financial stability. The design of integrated top-down stress tests that allow a mapping of the amplification mechanisms that may reinforce climate risks may serve as a helpful tool for supervisors.

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Appendix A – Data

Table A1: Description of variables used in the historical data sample of the micro and macro stress test models, together with their sources

Variable	Definition	Unit	Source
Micro model			
$PD_{i,t}$	Probability of default for firm *i* (median across bank-firm obs.) in year *t*	$PD_{i,t}$=ln(x/(1-x))	Bundesbank's credit register
$ROA_{i,t}$	Return on assets for firm *i* in year *t*: EBIT/total assets	%	Bundesbank balance sheet statistics for non-financial firms
$Leverage_{i,t}$	Total liabilities/total assets	%	Bundesbank balance sheet statistics for non-financial firms
$Interest\ expense\ ratio_{i,t}$	Interest expense/total assets	%	Bundesbank balance sheet statistics for non-financial firms
$Liquidity\ ratio_{i,t}$	Liquid assets/total assets	%	Bundesbank balance sheet statistics for non-financial firms
$Equity\ ratio_{i,t}$	Total equity/total assets	%	Bundesbank balance sheet statistics for non-financial firms
$Emissions\ intensity_{i,t}$	Greenhouse gas emissions (tonnes of CO_2)/total sales	Tonnes of CO_2 per million euro of sales	European Union Emissions Trading System (ETS), European Pollutant Release and Transfer Register (E-PRTR), ISS ESG, Eurostat
Macro model			
$PD_{s,q}$	Probability of default for sector *s* (volume-weighted mean across firm-level PDs) in quarter q	$PD_{i,t}$=ln(x/(1-x))	Bundesbank's credit register
GDP_q	German real gross domestic product in quarter q	Billion euro	Eurostat, real gross domestic product for Germany
$Long\text{-}term\ interest\ rate_q$	German 10-year sovereign bond yield	%	ECB Data Portal, average nominal yields for total government debt securities with zero coupon
$Inflation_q$	German consumer price index	Index	OECD, Consumer Price Index: OECD Groups: All Items Non-Food Non-Energy: Total for Germany
$Unemployment_q$	German unemployment rate	%	ECB Data Portal, unemployment rate, Germany
$Short\text{-}term\ interest\ rate_q$	1-year EURIBOR	%	ECB Data Portal, Euribor 1-year
$Equity\ prices_q$	German stock index	Index	De.finance.yahoo.com, DAX performance index
$Carbon\ price_q$	Emission price for one tonne of carbon dioxide or carbon dioxide-equivalent greenhouse gas	Price in euro per tonne of CO_2	Intercontinental Exchange for EU allowances

Table A2: Descriptive statistics for variables used in the historical data sample of the micro and macro stress test models

Variable	Obs.	Mean	Median	SD	10^{th} percentile	90^{th} percentile
Micro model						
$PD_{i,t}$	114,312	-5.231	-5.293	1.396	-7.012	-3.435
$ROA_{i,t}$	114,255	6.537	5.012	11.167	-2.958	18.710
$Leverage_{i,t}$	114,281	54.193	55.247	24.925	18.982	88.086
$Interest\ expense\ ratio_{i,t}$	111,801	1.574	1.270	1.292	0.219	3.322
$Liquidity\ ratio_{i,t}$	109,498	7.805	3.073	11.581	0.068	22.341
$Equity\ ratio_{i,t}$	110,011	33.468	30.814	21.652	6.129	64.815
$Emissions\ intensity_{i,t}$	27,913	76.930	11.390	609.045	4.360	162.370
Macro model						
$PD_{s,q}$	3,080	-4.441	-4.452	0.724	-5.261	-3.585
GDP_q	56	708.867	713.554	57.736	648.384	802.762
$Long\text{-}term\ interest\ rate_q$	56	3.343	2.820	1.893	-0.237	4.668
$Inflation_q$	56	93.872	94.788	7.610	84.792	105.178
$Unemployment_q$	56	7.481	6.600	2.464	3.470	10.130
Short-term interest rate	56	2.517	1.000	1.534	0.000	4.000
$Equity\ prices_q$	56	71.079	69.762	21.029	45.045	99.118
$Carbon\ price_q$	53	15.493	11.055	15.222	4.856	26.910

Table A3: Overview of economic sectors classified as carbon-intensive

NACE code	**Sector description**
A01	Crop and animal production, hunting and related service activities
A02	Forestry and logging
A03	Fishing and aquaculture
B05	Mining of coal and lignite
B06	Extraction of crude petroleum and natural gas
B07	Mining of metal ores
B08	Other mining and quarrying
B09	Mining support service activities
C17	Manufacture of paper and paper products
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
D35	Electricity, gas, steam and air conditioning supply
H50	Water transport
H51	Air transport

Notes: The NACE codes refer to the economic sector classification according to NACE Rev. 2 level 2. NACE is the statistical classification of economic activities in the European Community.

Table A4: Long-run multipliers for all variables used in the macro model for each sector

NACE sector	**GDP**	**LTIR**	**Inflation**	**UE**	**STIR**	**Equity price**	**Carbon price**	**GDP**	**LTIR**	**Inflation**	**UE**	**STIR**	**Equity price**	**Carbon price**
	QoQ	**QoQ**	**QoQ**	**QoQ**	**QoQ**	**QoQ**	**QoQ**	**YoY**	**YoY**	**YoY**	**YoY**	**YoY**	**YoY**	**YoY**
A01	-	-	-	-	-	-	-	-	-	-	-	-	-	-
A02	-0.056	0.001	-0.013	-	-	-0.558	-	-0.001	-	-0.009	-	0.007	-	0.149
A03	-0.019	0.007	0.017	0	-0.07	-0.015	-	-0.062	-	0.063	0	-0.069	-0.51	0.208
B05_09	-0.024	-	-0.057	-	-0.003	-0.414	-	-0.201	-	-0.029	-	-0.006	-	0.458
C10_12	-0.076	0	-0.182	-	-0.358	-0.754	0.03	-0.1	0.001	-0.142	0	0	-	0.002
C13_15	-	0.727	-	-	-0.571	-	-	-	-	-	-	-0.166	-0.005	0.586
C16	-0.007	0	-0.002	0	-0.321	-0.029	0.078	-0.026	0	0.011	-	-0.553	-0.019	0.007
C17	-	-	0.015	-	-0.159	-0.023	-	-0.388	-	0.38	-	-0.004	-0.026	0.546
C18	-	-	-0.003	0.002	0	-	0.042	-0.531	-	-0.463	-	-0.046	-	0.045
C19	-0.011	0	-0.076	-	-0.105	-0.022	-	-0.06	-	-0.136	0	-0.017	-0.544	0.094
C20	-	0.001	0.006	-	0	-0.086	-	-0.688	0	0.115	-	-	-0.033	0.441
C21	-0.076	-	-0.027	-	-	-0.41	0.004	-0.24	0	-0.028	-	0	-	0
C22	-0.009	0.066	-	-	-0.35	-0.006	0.047	-0.093	0.035	0.829	-	-0.128	-0.03	0.122
C23	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C24	-0.021	-	-0.253	-	-0.005	-	-	-0.285	-	-0.061	-	-0.013	-	0.086
C25	-	-	-	-	-0.007	-	0.065	-0.47	-	-0.015	-	-	-	0.038
C26	-	0.011	-0.178	-	0.018	-	0.013	-0.898	-	-	-	0.013	-	0.001
C27	-0.046	0	0.039	0	-0.276	-0.013	0.158	-0.124	0.015	0.431	-	-0.073	-0.044	0.163
C28	-0.005	-	-0.014	-	-0.08	-	0.411	-0.39	-	-0.091	-	-0.019	-0.751	0.006
C29	-0.034	-	0.019	-	-0.055	-0.26	0.026	-0.125	-	0.153	-	-0.198	-0.005	0.042
C30	-0.022	0.001	0.052	0	-0.007	-0.012	0.02	-1.05	-	0.233	-	-0.006	-0.011	0.117
C31_32	-0.01	0.001	-0.189	-	-0.013	-	0.356	-0.013	0.001	-0.029	-	-0.124	-0.495	0.066
C33	-0.371	-	-0.188	-	-0.006	-0.02	0.138	-0.033	-	-	-	-0.189	-	-
D35	-0.012	0.002	0.011	-	-0.067	-	-	-0.001	0	0.01	0	-0.027	-0.621	0.282
E36	-0.005	-	0.003	0	-0.055	-0.091	0.079	-0.31	-	0.679	-	-0.008	-0.031	0.044
E37_39	-0.081	-	-0.382	-	-	-0.051	-	-0.269	-	0.017	-	-	-0.24	0.187
F41_43	-	-	-	-	-	-	-	-	-	-	-	-0.393	-0.475	-
G45	-	-	-	-	-0.271	-	-	-0.026	-	-	-	-0.151	-	-

G46	-	-	-0.013	-	-0.377	-0.014	-	-0.91	-	-0.107	-	-	-	-
G47	-	-	0.706	-	-	-0.087	-	-0.893	-	-	-	-	-	-
H49	-	-	-	-	-	-	-	-	-	-	-	-	-	-
H50	-	-	-0.036	-	-0.061	-	0.088	-0.051	-	-0.408	-	0.006	-	-
H51	-	-	-0.011	-	0.009	-0.011	-	-1.326	0	0.024	-	0	-0.024	0.07
H52	-0.018	0.002	-1.264	0	0.012	-0.018	0.135	-0.982	-	0	0	0.004	-0.016	0.062
H53	-0.605	-	-0.04	-	-0.062	-0.07	0.007	-0.007	-	-0.012	-	-0.434	-0.922	0.008
I55_56	-	-	-0.001	0	0.004	-0.017	0.011	-1.252	-	0.073	-	0.012	-0.499	0.006
J58	-	-	-	-	-0.101	-	0.02	-0.991	-	1.12	-	0.085	-0.207	0.04
J59_60	-0.006	-	0.031	-	-	-0.01	0.005	-0.396	0.54	0.004	-	-0.547	-0.439	0.279
J61	-0.025	0.001	0.244	-	-0.361	-0.013	0.024	-0.056	-	0.372	-	-0.008	-0.029	-
J62_63	-0.059	-	0.065	-	-0.436	-0.065	0.001	-0.187	-	0.079	-	-0.002	-0.201	-
L68	-	-	0.011	-	0.022	-0.059	0.022	-	-	-0.176	-	0.034	-1.003	0.002
M69_70	-0.324	-	-0.038	-	-	-	0.536	-0.109	-	-	-	-	-0.476	-
M71	-0.023	-	-0.222	-	-0.042	-0.013	0.086	-0.028	0.001	-0.094	-	-0.014	0	0.654
M72	-0.003	1.035	-0.046	0	-0.771	-0.058	0.004	-0.012	0.027	-0.021	0.003	-0.368	-	0.001
M73	-	-	-	0.212	-	-	-	-	0.578	-	-	0.519	-	-
M74_75	-0.004	-	-0.009	-	-0.091	-0.194	0.002	-0.001	-	0	-	-	-0.217	0.144
N77_82	-0.067	-	0.205	-	-0.006	-0.005	0.035	-0.151	-	0.04	-	-0.01	-0.013	0.032
O84	-	-	-	-	-	-	-	-	-	-	-	-0.494	-	-
P85	-0.024	-	-0.041	0	-0.222	-0.122	0.065	-0.014	0.001	0.58	-	-0.003	-0.945	0.022
Q86_88	-0.302	-	0.331	-	-0.025	-0.246	0.257	-0.18	0	0.218	-	-0.002	-0.154	0.442
R90_S96	-0.071	0.001	-0.147	0	-0.015	-0.034	0.047	-0.661	0	0.01	-	-0.003	-0.118	0.217

Notes: "-" implies that the variable is not included in the surviving model space. If no long-run multipliers are given for a sector, this implies that the benchmark model was used for this specific sector.

Appendix B – Analytical steps

1. **Firm-level breakdown of macro climate scenarios (micro-level approach)**[47]

Interest expense

Short-term interest rate changes from the climate scenarios $\Delta STIR^{scenario,t}$ affect the InterestRate_i payable by the enterprise. Changes in debt impact on interest expense with a one-year lag.

$$InterestExp_i^{scenario,t} = Debt_i^{scenario,t-1} * (InterestRate_i^{scenario,t-1} + \Delta STIR^{scenario,t}) \,, \qquad \text{(B1)}$$

where

$$InterestRate_i^{scenario,t-1} = InterestExp_i^{scenario,t-1} / Debt_i^{scenario,t-1} \qquad \text{(B2)}$$

Net profits for the financial year

Net profits for the financial year are derived from EBIT and interest expense, with a flat *tax* rate of 30% being applied. The *payout* rate takes a value of 40% in variants B1 and of 80% in variants B2:[48]

$$NetProfits_i^{scenario,t} = \left(EBIT_i^{scenario,t} - InterestExp_i^{scenario,t}\right) * (1 - tax) * (1 - payout). \qquad \text{(B3)}$$

Between 2010 and 2022, payout rates of listed stock corporations in Germany ranged from 38% to 45% (variants B1). However, key P&L items are not modelled; in reality, these would generally lower net profits for the financial year. For this reason, variant B2 uses a payout rate of 80%.

Cash needs

Outflows are serviced out of liquidity, with a positive EBIT assumed to have a liquidity-increasing effect. Cash needs arise when firms are unable to service cash outflows resulting from interest expense (and a possibly negative EBIT). Firms then have to take on debt:

$$CashNeeds_i^{scenario,t} = \min(0;\ Liquidity_i^{scenario,t-1} + EBIT_i^{scenario,t} - Interest\ expense_i^{scenario,t}) \qquad \text{(B4)}$$

[47] Some of the proposed computations are based on Tressel and Ding (2021) and Demmou et al. (2021).
[48] Taxes and payouts are deducted only if the value left after subtracting interest expense from EBIT is positive.

Debt (interim)

If cash needs are identified, this has the effect of increasing debt. Climate-related incremental investment by firms is likewise assumed to be fully debt-financed:

$$InterimDebt_i^{scenario,t} = Debt_i^{scenario,t-1} + \left(CashNeeds_i^{scenario,t} * (-1)\right) + \Delta Invest_{s,i}^{scenario,t}. \tag{B5}$$

Liquidity (interim)

In addition to EBIT and interest expense, possible tax outflows and payouts to shareholders will also affect liquidity. Covering cash needs cannot cause liquidity to turn negative:

$$InterimLiquidity_i^{scenario,t} = (Liquidity_i^{scenario,t-1} + EBIT_i^{scenario,t} - InterestExp_i^{scenario,t} + CashNeeds_i^{scenario,t} * (-1)) * (1 - tax) * (1 - payout). \tag{B6}$$

Debt reduction

Firms are able to repay debt if they have sufficient excess liquidity to do so. In this respect, the firm's liquidity ratio and debt ratio (each of which relates to total assets, *TA*) in the starting year are regarded as target ratios that the firm takes into account throughout the scenario horizon:

$$DebtReduction\ _i^{scenario,t} = (ExcessLiquidity_i^{scenario,t} + ExcessDebt_i^{scenario,t})/2, \tag{B7}$$

where

$$ExcessLiquidity\ _i^{scenario,t} = \min(0; \left(\frac{InterimLiquidity_i^{scenario,t}}{TA_i^{scenario,t-1}} - \frac{Liquidity_i^{t=0}}{TA_i^{t=0}}\right) * TA_i^{scenario,t-1}) \tag{B8}$$

and

$$ExcessDebt\ _i^{scenario,t} = \min\left(0; \left(\frac{InterimDebt_i^{scenario,t}}{TA_i^{scenario,t-1}} - \frac{Debt_i^{t=0}}{TA_i^{t=0}}\right) * TA_i^{scenario,t-1}\right). \tag{B9}$$

The firms' final liquidity and debt therefore only come about after a possible debt reduction:

$$Liquidity_i^{scenario,t} = InterimLiquidity_i^{scenario,t} - DebtReduction\ _i^{scenario,t} \tag{B10}$$

$$Debt_i^{scenario,t} = InterimDebt_i^{scenario,t} - DebtReduction\ _i^{scenario,t}. \tag{B11}$$

Equity

Two different modelling decisions are used to calculate firms' equity. Modelling decision (B12) envisages that equity evolves in line with net profits for the financial year:

$$Equity_i^{scenario,t} = Equity_i^{scenario,t-1} + NetProfits_i^{scenario,t}. \tag{B12}$$

Modelling decision (B13), meanwhile, assumes that equity moves in line with sectoral equity prices from the scenarios:

$$Equity_i^{scenario,t} = Equity_i^{scenario,t-1} * \left(1 + \Delta EQP_s^{scenario,t}\right). \tag{B13}$$

In the "modelling decision" variant, equity grows when taxed profits are retained or it is depleted by losses. However, because profits and losses are modelled only partially and discretionary decisions by firm owners (capital increases or withdrawals) can also have an impact on equity, in modelling decision B13 equity evolves in line with the sector-specific equity price paths (EQP) specified in the scenarios. In this case, equity stands more for market expectations of future profits.

Total assets

Changes in debt and liquidity affect total assets.

$$\begin{aligned} TA_i^{scenario,t} = {} & TA_i^{scenario,t-1} + InterimDebt_i^{scenario,t} - Debt_i^{scenario,t-1} + InterimLiquidity_i^{scenario,t} \\ & - Liquidity_i^{scenario,t-1} - DebtReduction_i^{scenario,t} . \end{aligned} \tag{B14}$$

2. Calculation of scenario-dependent LGDs

Micro approach

LGDs evolve in line with firm-specific equity ratios, with a reduction in equity ratios impacting negatively on LGDs. The adverse effect is stronger given a lower firm-specific $CollateralRatio_i$.[49]

$$\begin{aligned} LGD_i^{scenario,t} = {} & \min[LGD_i^{scenario,t-1} * \max[(1/(1 \\ & + (DeltaEQRatio_i^{scenario,t} * \left(1 - \frac{CollateralRatio_i}{2}\right)))),1],1], \end{aligned} \tag{B15}$$

[49] If a conservative modelling approach is used, LGDs cannot decline (max function); at the same time, it is ensured that the LGDs do not exceed 100% (min function).

where for

$$DeltaEQRatio_i^{scenario,t} = \frac{Equity_i^{scenario,t}}{TA_i^{scenario,t}} / \frac{Equity_i^{scenario,t-1}}{TA_i^{scenario,t-1}} - 1 \quad \text{(B16)}$$

the calculation follows the steps set out in Appendix B1.

Macro approach

The approach used to determine PD paths (see Section 3.2) is also used to determine LGD paths. However, as data availability is generally more limited than for PDs, only an aggregate add-on is derived in the firm portfolio for the LGDs.

The LGD paths determined in the micro and macro approaches are transformed into LGDs using the procedures described in Section 3.3 – in other words, as with the PD paths, the first step is to fill data gaps in line with the depicted schema, followed by the non-linear transformation of the LGD paths.

3. Calculation of expected and realised credit losses

The additional risk provisioning required/the expected (relative) loss ratio is obtained by calculating the difference between losses in the stress scenario and losses in the baseline scenario and expressing this relative to the loan volume. Relative losses or climate-related losses thus constitute losses that go beyond losses in the baseline scenario. They roughly correspond to the economic credit losses required or the general credit losses arising from climate risks:

$$EL\_Ratio^t = \frac{PD^{stress,t} * LGD^{stress,t} * TotalLoans - PD^{base,t} * LGD^{base,t} * TotalLoans}{TotalLoans} \quad . \quad \text{(B17)}$$

Furthermore, the materialisation of credit defaults throughout the observed scenario horizon can be simulated for each individual bank, meaning that the ex post adjustment requirements can be estimated in the form of additional credit losses (ACLs):

$$\mathrm{ACL}_{p90|p99} = \mathrm{ACL}_{p90|p99}^{stress} - \mathrm{ACL}_{p90|p99}^{base} \ , \quad \text{(B18)}$$

$$\mathrm{ACL}_{p90|p99}^{stress} = p_{90|99,k=1,000}[\textstyle\sum_i \sum_{t=1}^{t\_default}(\mathrm{Default}[0|1]^{\mathrm{stress,i,t}} * LGD^{stress,i,t} * \mathrm{EaD}^{\mathrm{stress,i,t}}) - \sum_i \sum_{t=1}^{t\_default} (PD^{stress,i,t} * LGD^{stress,i,t} * EaD^{stress,i,t})]/TotalLoans \ , \quad \text{(B19)}$$

$$\mathrm{ACL}_{p90|p99}^{base} = p_{90|99,k=1{,}000}\left[\sum_i \sum_{t=1}^{t\_default}(\mathrm{Default}[0|1]^{\mathrm{base,i,t}} * LGD^{base,i,t} * \mathrm{EaD}^{\mathrm{base,i,t}}) - \sum_i \sum_{t=1}^{t\_default}(PD^{base,i,t} * LGD^{base,i,t} * EaD^{base,i,t})\right]/TotalLoans\ . \tag{B20}$$

The subscript "$p90|p99$" designates the calculation of both the 90th and 99th percentiles of the 1,000 simulation runs (index: "k") at the individual bank level. A loan default is indicated by "$Default[0|1]$" and the corresponding point in time by "$t\_default$".[50] The index "i" indicates the individual loan granted by a bank to a firm. "$EaD^{i,t}$" denotes the credit exposure of the loan in question at point in time "t".

[50] To determine whether a default has occurred, a random number in the interval [0, 1] is drawn. If the value of the random number drawn is below the loan's projected PD for this period, it is classified as "defaulted".