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A Method to Incorporate Transition Risk Stress Testing Into Probability of Default (PD) Models for Retail Portfolios

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ABSTRACT

Climate risk is one of the type of risks in a bank's portfolio which is not fully recognized, and its impact on the future overall risk changes is hidden due to lack of sufficient knowledge at the moment. One of the most common data comes from Network for Greening the Financial System (NGFS) scenarios related to climate change (physical risk) and climate policy and technology trends (transition risk). In the paper we focused on the transition risk scenarios and their impact on the economy and in particular on credit risk. Our main goal was to check the tendency in the probability of default (PD) default prediction in relation to climate risk potential future scenarios. We used data related to credit risk observed in Southern Europe banks for mortgage products for the years 2003–2019. Based on PD models we predicted the changes in the PD parameter over many years ahead by considering the set of scenarios collected in NGFS data. We selected the two scenarios 'carbon tax revenue from the residential and commercial sector' and 'electricity price at the final level in the transportation sector' for building the final models. From the PD logit model and linear predictors for the PD model we found that the main determinants predicting PD correlating with NGFS scenarios are LTV, customer income, unemployment rate, and crude oil prices. The quality of univariate models is above average, and the quality of the PD model is on an average level. The proposed models can be used in banking as stress tests in climate risk management.

JEL classification: G17, G21

Keywords: stress tests, climate risk, NGFS data

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1. INTRODUCTION

Climate risk is one of the types of risks in a bank's portfolio which currently cannot be easily quantified, and its impact on the future overall risk changes is hidden due to lack of sufficient knowledge. In particular, there are neither reliable and representative historical data nor ESG information and developed models for climate risk estimation. This is widely explored in number of papers (Baudino & Svoronos, 2021). Stress testing is currently the only tool that takes into account the long-term materialisation characteristics of climate risk. Standard PD models used for credit risk are not useful for climate risk because they are mostly based on historical data (which in turn do not represent the characteristics of this risk). In our paper, we analyse retail mortgage portfolios from the Southern Europe. The reliable PD prediction and the actual impact of the transition risk on the portfolio risk is a very important goal for the banks in order to ensure that their strategy is aligned with the Net Zero targets by 2050 as well as helping in the admission criteria to transition to a low-carbon economy. The future impact of both the climate transition processes and climate change are very important for the estimation of banks' capital (ECB, September 2021). Transition risk scenarios mainly focus on the transition from fossil fuels, carbon-intensive production and consumption towards emission-neutral alternatives. Those scenarios are defined for different variants and include transition risk drivers such as energy consumption, energy prices per sector and energy sources, carbon taxes and prices, energy consumption, carbon sequestration, CO_2 emissions, GDP and crop prices. The purpose of the paper is to check and propose a reliable modelling approach for the PD risk parameter based on climate transition risk scenarios. We aim to verify tendencies in the PD prediction in relation to the climate risk scenarios using NGFS database (Phase III). Ultimately, we take into account internal information for debtors along with macroeconomic variables and the transition scenarios. In our research we use on internal and external data. The sample consists of the portfolio data for years 2003–2019 where we **merged the customer related information and macroeconomic data with transition risk scenarios** to predict the trend of the portfolio risk in the future. Analysis based on NGFS scenarios and on real data add value to existing research literature on climate risk.

2. LITERATURE REVIEW

Climate risk is mostly connected to credit risk and for now it is not yet recognised and classified as stand-alone risk in banking. Transition risk and physical risk influence credit risk by deteriorating the creditworthiness of borrowers. This relation was defined by Capasso at el. (2020) by using distance-to-default measure and connecting this measure to an enterprise's carbon emission. According to the authors, the higher the emission, the higher the risk of default. This observation was also supported by Gianfrate (2020). The distance-to-default is a widely used market-based measure of corporate default risk. The authors also confirms that it is negatively associated with the amount of a firm's carbon emissions and carbon intensity. Companies with a high carbon footprint are seen as more likely to default.

Generally, enterprises with a higher impact on the climate and the environment must also consider the higher cost of loans and lower ratings (Kurowski, Sokal 2023; Bauer, Hann 2010). Also, the regulator recommends including climate risk at each stage of the credit underwriting process (ECB 2020).

Identification and measurement of physical and transition risk is difficult due to lack of data and experts in this field. Emissions are measured on the level of the customer's and bank's portfolio. Climate risk is very much sector-specific. Banks typically use so-called risk maps recommended by the EBA (2020). High-risk sectors must be more deeply and more frequently monitored. Another way to measure climate risk is the stress test. Using stress test scenarios in climate risk is complicated due to the requisite long time-horizon (e.g., 30 years). Due to this requirement, the NGFS data base, one of the most common data bases used for predicting future climate scenarios, are included in the NGFS data. NGFS is a group of 65 central banks and supervisors committed to sharing best practices, contributing to the development of climate- and environment-related risk management in the financial sector.

Stress testing is an important tool in the context of risk management. Using climate risk scenarios provided by NGFS unable to incorporate climate risk into risk management. Incorporating climate risk by different tools such as scoring models would be difficult and not intuitive, although is it better than other commonly used risk measurement tools. Climate change and the transition to net zero carbon emissions pose indirect risks to the financial sector by increasing risk for households and businesses. Environmental and climate-related risks are among ECB Banking Supervision's strategic priorities for 2022–24.[2]

In 2022 the ECB conducted a climate risk stress test and the results show that banks do not yet sufficiently incorporate climate risk into their stress-testing frameworks and internal models. For both banks and supervisors this was a learning exercise to assess the sector's preparedness for managing climate risk. In the report, the ECB also identified best practices for dealing with this risk effectively.[3] Best practices also serve as an important part of climate education for the banking sector to facilitate the proper management of climate risk and to select the appropriate tools to measure it, for example, stress testing.

3. DATA DESCRIPTION

Scenarios included in NGFS data are related to climate change (physical risk), climate policy and technology trends (transition risk). We use phase III scenarios (NGFS, 2022b). We focussed on the transition risk scenarios and their impact on the economy and in particular on credit risk. Scenarios related to the transition risk can be grouped into four segments.

Orderly scenarios which assume that climate policies are introduced early and tend to become more and more rigorous.

- Net Zero 2050, which aims to limit global warming to 1.5°C, reaching net zero CO_2 emissions around 2050. Strict climate policies were introduced immediately. Carbon Dioxide Removal (CDR) will be used to accelerate process of decarbonisation. It is estimated that there is a 50% chance that those scenarios will materialise. Physical risks are low but transition risks are high.
- Below 2°C scenario, which assumes progressive increase of the stringency of climate policies. There is 67% chance of that this scenario will materialise. CDR use will remain relatively low. Net-zero CO_2 emission is expected to be reached by 2070. Both physical and transition risks are low.

Disorderly scenarios assume that climate policies are introduced with delay or they are divergent across countries and sectors.

- Divergent net-zero is similar to Net Zero 2050, but it assumes divergent policies across sectors and a quicker phase out of fossil fuels. Climate policies are stricter in the transportation and building sectors. Lack of coordination of policies between sectors will result in a high burden on consumers as opposed to energy supply and industry sectors where policies will be less stringent. Use of CDR will be lower than in Net Zero 2050. There is 50% chance of limiting global warming to below 1.5°C. This scenario has higher transition risk than Net Zero 2050, but has the lowest physical risks of all NGFS scenarios.
- Delayed transition assumes that no global emissions are to decrease until 2030. After 2030, rigid policies will be needed to limit global warming to below 2°C. CDR availability will be low, which will cause carbon prices to be higher than in Net Zero 2050. Therefore, emissions will exceed the carbon limits at the beginning and decline more rapidly after 2030 in order to ensure a 67% chance of limiting global warming to below 2°C. This scenario has a higher transition and physical risk than Net Zero 2050 and Below 2°C scenario.

Hot-house world scenarios assume that some climate policies are introduced in a restricted area.

- Nationally Determined Contributions (NDCs) assumes that climate policy changes will be moderate and vary greatly across countries. Climate ambition reflected in the conditional NDCs at the beginning of 2021 are expected to continue throughout the 21st century. Emissions should decline, but will lead to 2.6°C global warming. This will result in moderate to severe physical risks and low transitions risks
- Current Policies assume that currently implemented climate policies will remain in place. Emissions are expected to grow until 2080, causing about 3°C global warming. This scenario includes climate changes that cannot be reversed. This will result in severe physical risks and almost no transition risks.

Too little, too late scenarios assume no effort to counteract the climate change. This will result in severe physical risks and severe transition risks.

[2] ECB Banking Supervision – Supervisory priorities for 2022–2024 (europa.eu)

[3] 2022 climate risk stress test (europa.eu)

Table 1 summarises the transition risk and physical risk properties for the mentioned segments.

Table 1
NGFS Scenarios summary for transition and physical risk

		Physical risk	Transition risk			
Category	**Scenario**	**Policy ambition**	**Policy reaction**	**Technology change**	**Carbon dioxide removal** *	**Regional policy variation** *
Orderly	Net Zero 2050	1.4°C	Immediate and smooth	Fast change	Medium-high use	Medium variation
	Below 2°C	1.6°C	Immediate and smooth	Moderate change	Medium-high use	Low variation
Disorderly	Divergent Net Zero	1.4°C	Immediate but divergent across sectors	Fast change	Low-medium use	Medium variation
	Delayed Transition	1.6 °C	Delayed	Slow / Fast change	Low-medium use	High variation
Hot house world	Nationally Determined Contributions (NDCs)	2.6°C	NDCs	Slow change	Low-medium use	Medium variation
	Current Policies	3°C +	Non-currente policies	Slow change	Low use	Low variation

Colour coding indicates whether the characteristic makes the scenario more or less severe from a macro-financial risk perspective*

- Lower risk
- Moderate risk
- Higher risk

Source: NGFS.[4]

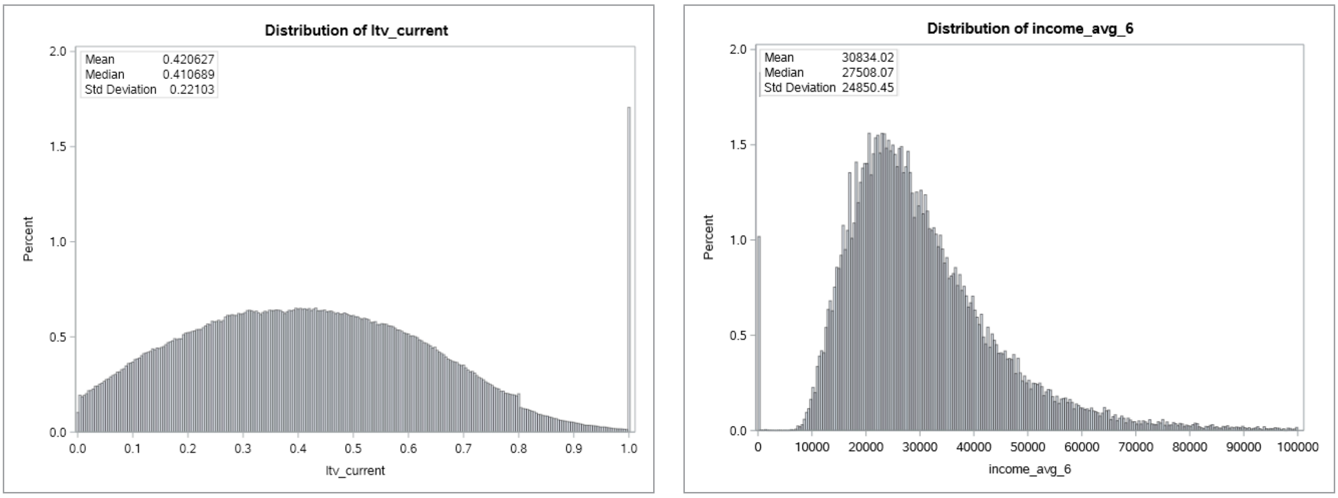
The base data set we used to build the climate risk model is data related to credit risk observed in portfolio of mortgages of the Southern Europe banks. Data covers the period from 2003-12-31 to 2019-09-30. We propose a PD model where the target variable is the binary default flag which indicates entering into the default state within the next 12 months after data assessment.

Apart from the basic trigger of default used by banks, which is the delay in payment over 90 days (90 DPD+), we take into account many other default triggers. Various data sources are used as the input for potential explanatory variables. Modelling data includes different information such as customer-oriented data, macroeconomic data, basic financial ratios, transactional data, behavioural data and collateral features. Our main dataset contains almost 5,000,000 observations, which would make it time-intensive and inefficient for the performance of logistic regression. Therefore, we prepared around 150,000 observations from randomly selected samples (stratified on default) and ran logistic regression on it. The data was divided into the training and test data sets where the training data set includes 70% of the entire sample. Some data transformations and data quality checks were applied prior to model building as well as qualitative analysis, which helped to remove unintuitive (not business explainable) and unusable variables. All variables with the share of missing values greater than 10% were removed from the sample as unreliable for the predict default flag. The missing values for other variables were imputed with the most frequent values (according to distribution). The average observed default rate in the analysed portfolio is 0.534%. The distribution of key portfolio characteristics, such as LTV, income, and the main macroeconomic variables used in the models, are shown in the figures below (see Figures 1–3). The analysed portfolio is characterised by average income around 30,000 EUR (last 6 months) and the current LTV of around 42%. The unemployment rate changes smoothly over the analysed period while crude oil prices more volatile.

[4] https://www.ngfs.net/sites/default/files/medias/documents/ngfs_climate_scenarios_for_central_banks_and_supervisors_.pdf.pdf

Figure 1

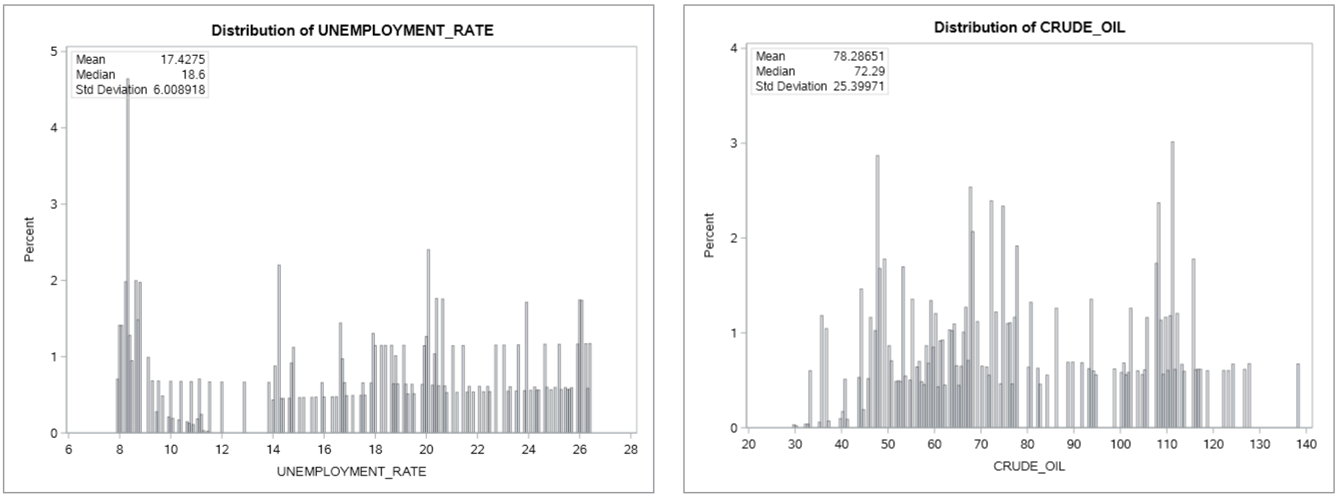
Key characteristics distributions of the current LTV and average income from the last 6 months



Source: Authors' calculation.

Figure 2

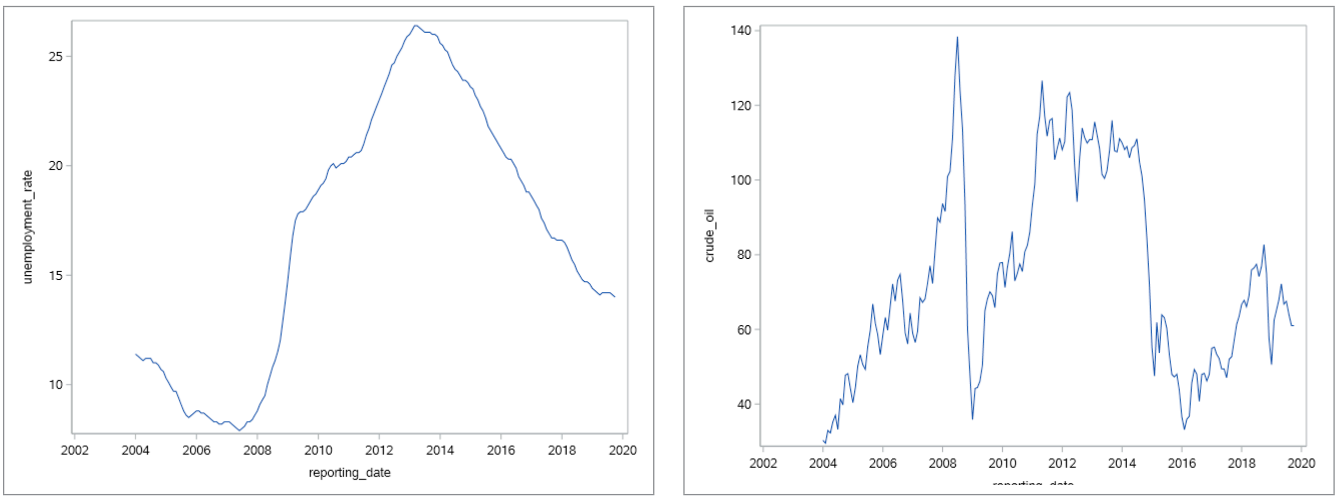
Distributions of the macro variables Unemployment Rate and Crude Oil prices



Source: Authors' calculation.

Figure 3

Historical trends of Unemployment Rate and Crude Oil prices, 2004–2020



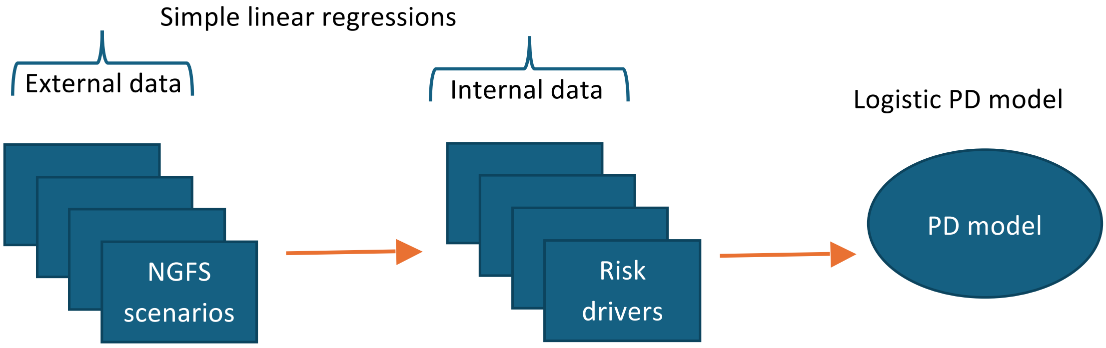
Source: Authors' calculation.

4. MODEL DESCRIPTION

The purpose of the paper is to check and propose a reliable modelling approach for the PD risk parameter based on the climate transition risk scenarios. All input scenarios from NGFS data are filtered out based on reliable data, including the control of missing values, then the simple linear regression models are built, where remaining NGFS scenarios are independent variables in the models and all considered risk drivers are target variables.

The modelling approach based on internal or external data are shown in Chart 1.

Chart 1
Modelling approach



Source: Authors' elaboration.

In the first step, the PD logistic models based on both the customer variables and macroeconomic variables are built. Those models are constructed on the bank's internal data. Macroeconomic variables are included into the sample based on quarterly data. We built two alternative models, because all macroeconomic variables are highly correlated and could not be included in one model.[5] The first model is based on the unemployment rate (UR) and the second on the crude oil prices (CO). After building a few initial models we noticed that incorporating information about the average savings and the average income in the same model leads to nonintuitive coefficients signs that could be caused by correlation. That's why we split the main models into two separate ones of which one includes the average savings and the second one the average income. Having checked the results, we can propose the two separate models with UR variable and with CO variable.

PD in the models can be expressed by two alternative formulas as follows:

$$PD = \frac{1}{1 + \exp\left(-\left(a_0 + a_1 \cdot UR + \sum_{i=1}^{k_1} a_i \cdot X_i\right)\right)} \qquad [1]$$

$$PD = \frac{1}{1 + \exp\left(-\left(b_0 + b_1 \cdot CO + \sum_{i=1}^{k_2} b_i \cdot X_i\right)\right)} \qquad [2]$$

where:
X_i is a risk driver based on the customer information,
UR, CO are independent macroeconomic variables in the model,
a_i, b_i are the linear model coefficients.

[5] We considered also other macroeconomic variables, such as GDP and interest rates, but the latter is not easy to use in models due to negative interest rates in recent history.

In the second step transition scenarios are assigned to all risk drivers from the two main logistic models.

$$X_i = a_{i,j} + b_{i,j} \cdot S_j + \varepsilon_i \qquad [3]$$

where:
X_i is a risk driver from the PD logistic model,
S_j is a j-th transition scenario,
$a_{i,j}$, $b_{i,j}$ are the linear model coefficients,
ε_i is the error term.

The final model is a combination of the above formulas where the predicted variables X_i are the input to the main logistic models (formulas [1] and [2]).

5. MODELLING RESULTS

Taking into account the high correlation between macroeconomic variables, we decided to select the following two alternative models based on the most predictive macroeconomic variables, such as: unemployment rate (UR model) and crude oil prices (CO model). It is worth mentioning that we also considered other macroeconomic variables such as interest rates, GDP, and House Price Index, but due to high correlation and poor prediction power those variables were not included. Additionally, the following customer variables from the internal data had high predictive power: average income in the last 6 months, current LTV and average savings in the last 3 months.

The following tables (see Tables 2–4) show the models including estimators and test statistics. All variables are intuitive and significant on the 0.01 significance level.

The AUC of models are 0.7313, 0.6209 and 0.6081 respectively. The second and the third model that use the average income are on the border of their statistical acceptance but are used as an alternative to discussion in our research. The correlation of variables in the models based on the signs of estimators with the default flag is in line with business intuition, which is a desired property of those models. The following two figures (see Figure 4) present ROC curves for the final models.

Table 2
Model 1. Estimators for the UR model with the average savings

Parameter	Estimate	Standard deviation	Wald statistic	p-value
Intercept	-6.69060	0.16990	1551.3020	<.0001
UNEMPLOYMENT_RATE	0.06260	0.00670	87.2961	<.0001
ltv_current	0.96370	0.15710	37.6400	<.0001
F_SAVINGS_3M	-0.00035	0.00004	78.7078	<.0001

Source: Authors' calculation

Table 3
Model 2. Estimators for the UR model with the average income

Parameter	Estimate	Standard deviation	Wald statistic	p-value
Intercept	-6.47970	0.19130	1147.6870	<.0001
UNEMPLOYMENT_RATE	0.04750	0.00673	49.8133	<.0001
income_avg_6	-0.00002	0.00000	34.6797	<.0001
ltv_current	1.34180	0.15670	73.3392	<.0001

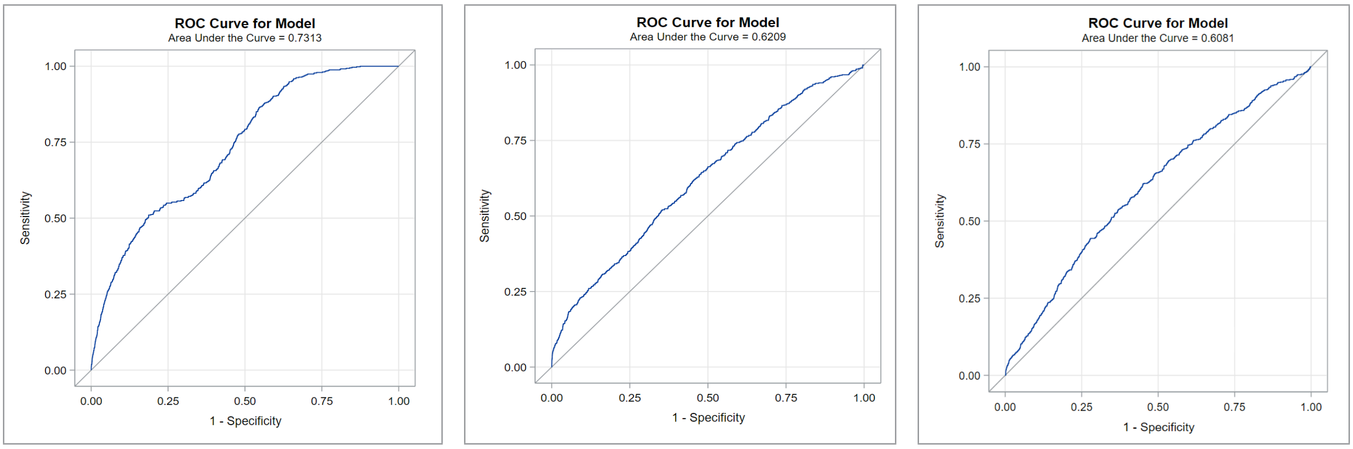
Source: Authors' calculation

Table 4
Model 3. Estimators for the CO model

Parameter	Estimate	Standard deviation	Wald statistic	p-value
Intercept	-5.74800	0.16380	1231.0810	<.0001
CRUDE_OIL	0.00951	0.00161	34.9118	<.0001
income_avg_6	-0.00002	0.00000	35.6741	<.0001

Source: Authors' calculation

Figure 4
ROC curves for logistic regression models: UR model with average savings (AUC=0.7313), UR model with average income (AUC=0.6209) and CO model with AUC=0.6081



Source: Authors' calculation

Based on the PD models we can predict the changes of the PD parameter in the future considering the set of scenarios collected in the NGFS data. Transition risk scenarios allow us to estimate an impact of climate policies on PD's prediction by incorporating them into the model structure. We built simple regression models based on the formula [3] shown in the previous section that predicts model variables for each scenario separately until 2050. For this auxiliary modelling process, we built over 10,215 linear regression models with one explanatory variable, which results from the number of scenarios (2043) and target variable that is one of the 5 risk drivers included in the logistic models. For each scenario and each of the three basic PD models, the average R-squared ratio from all the univariate models for risk drivers was calculated. One should be careful to use quantitative ratio such as R-squared as the only one measure for the scenario selection. Unfortunately, the historical data are still of inferior quality and not representative to the current years to use them without additional business expert checks. That is why the basic criteria to select the final scenario were both R-squared ratio and explainability of results in terms of signs of univariate model coefficients and the behaviour of PD prediction. We checked all the scenarios for the UR model based on the average savings, UR model based on the average income and CO model, separately. Only UR model based on the average savings met quantitative assumptions for the R-squared thresholds above 40%. Based on the calculated R-squared ratio we can select the most desirable scenarios that guarantee the best average and intuitive results. Based on the R-squared we selected the following scenarios:[6]

- Price_Agriculture_Non_Energy2084 (R^2=53.80%)
- Secondary_Energy_Electricity1348 (R^2=35.48%)

that meet the highest quantitative and explainability requirements. The first scenario the weighted average price index of non-energy crops (Index (2010=1)) and the second scenario - the net electricity production from natural gas (numbers of those scenarios just give the position in NGFS database).

For comparison, the top 10 scenarios in terms of R-squared ratio only are shown in Table 5.

[6] NGFS scenarios description: https://www.ngfs.net/sites/default/files/medias/documents/ngfs_climate_scenarios_for_central_banks_and_supervisors_.pdf.pdf

Table 5
Top 10 scenarios with highest R-squared ratio

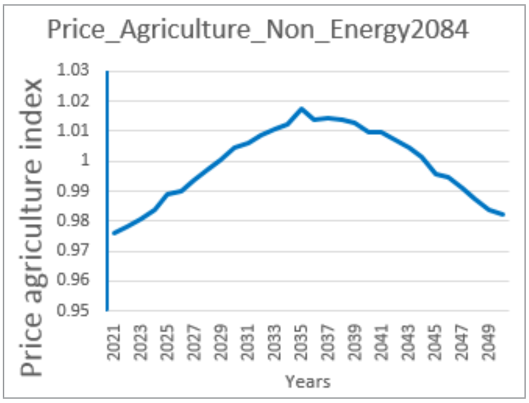
Scenario	R-squared
Final_Energy_Heat_DNZ1440	0.8352
Secondary_Energy_Electricity1686	0.8347
Carbon_Sequestration_CCS_Bio1904	0.8304
Final_Energy_Heat_NZ20502306	0.8296
Final_Energy_Industry_DT1228	0.8281
Revenue_Government_Tax_Carbo1247	0.8275
Primary_Energy_DT1230	0.8251
Primary_Energy_CP0647	0.8244
Primary_Energy_Fossil_w_o_CC1681	0.8238
Primary_Energy_NDC1950	0.8234

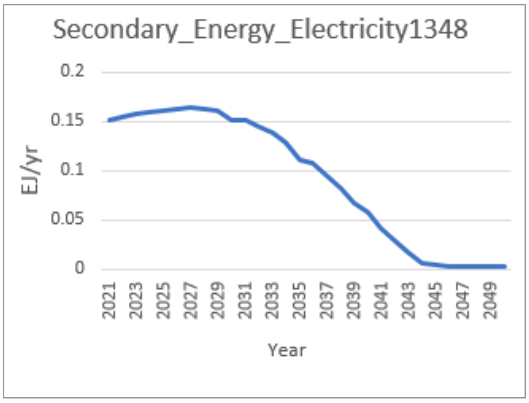
Source: Authors' calculation

It follows that there is still a high probability of overfitting the univariate models to predict risk drivers from the scenarios.

The trends over time for the two selected scenarios (values of price agriculture index and net electricity production from natural gas) are shown in Figure 5.

Figure 5
The predicted trends of the selected scenarios up to the year 2049





Source: Authors' calculation

The curves show that the expected future values for the price index and the net electricity production increase until 2027–2032 and then decrease over time. The specificity of the above scenarios determines the prediction of the main model risk drivers. The growth in the scenario based on price index is slower than the second one what is intuitive since the first scenario belongs to Hot House World category, while the second scenario to the Disordered category.

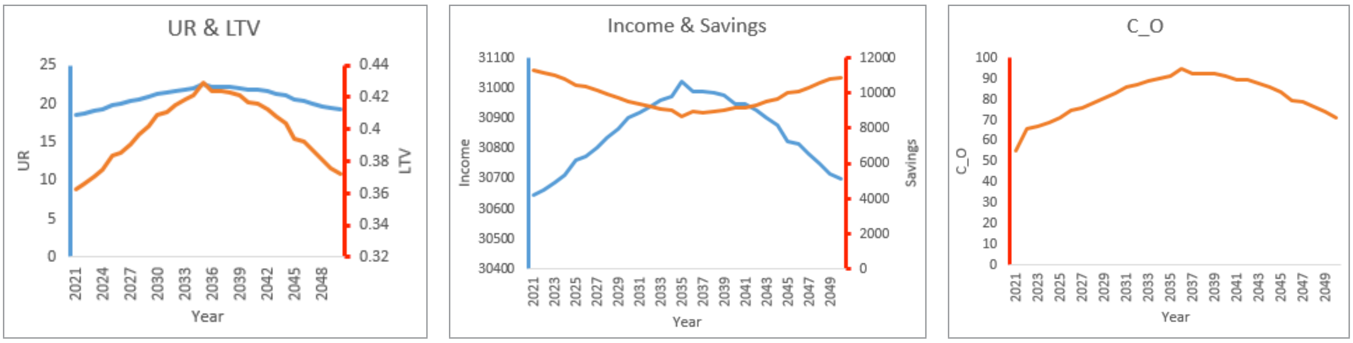
The UR models are described by the following results:

- predictions of the univariate linear regression models based on the two selected scenarios (Figure 6 and Figure 7) – predicted future variables are the inputs to run the two main logistic models that predict the final PD many years ahead,
- R-squared and estimators for the linear models (Table 6 and Table 7).

At the end the predicted PD values from the main model until 2049 (Figure 8) are calculated.

The following results have been obtained for the scenario based on the price index.

Figure 6
Estimated trends for variables used in models based on the scenario 'Price_Agriculture_Non_Energy2084'



Source: Authors' calculation. UR – unemployment rate, LTV – Loan to Value, CO – Crude Oil prices

The variables UR, LTV, CO and income receive the maximum value in 2035 and then decrease over time. The savings variable has a different trend with a minimum in 2035 but increases over time. All the above variables have intuitive trends apart from income. For this reason, we ultimately decided to omit the UR model based on the average income in order to predict the final PD.

Table 6
Slope estimators in the auxiliary regression models and appropriate R-squared ratios for model variables

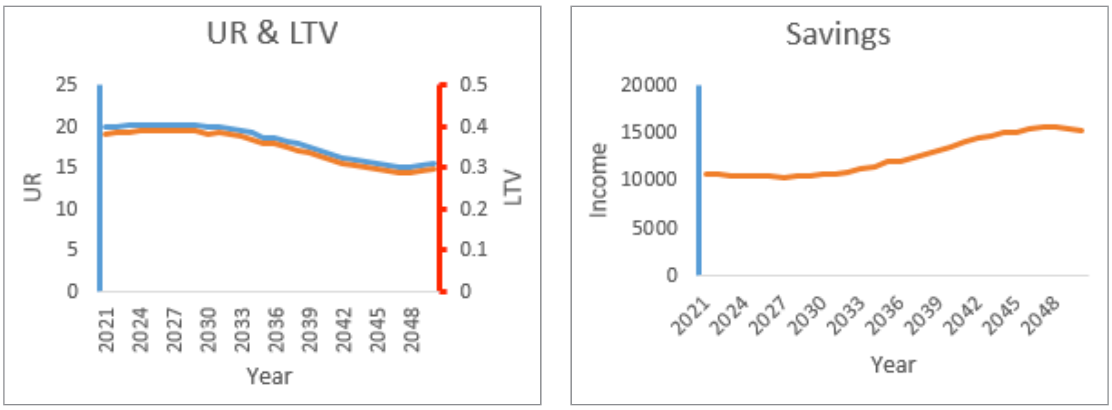
Variable	Scenario	
	Price_Agriculture_Non_Energy2084	
	R^2	estimate
Model UR		
UNEMPLOYMENT_RATE	0.2463	94.1276
ltv_current	0.4170	1.5976
F_SAVINGS_3M	0.9510	-61610.9572

Source: Authors' calculation

The next results have been obtained for the scenario based on the net electricity production from natural gas.

Similarly to the scenario previously analysed, two macroeconomic variables below have a maximum value in 2029, which then decreases until 2048. The savings variable also has a stable trend until 2023, which then increases until 2048.

Figure 7
Estimated trends for model variables based on scenario 'Secondary_Energy_Electricity1348'



Source: Authors' calculation

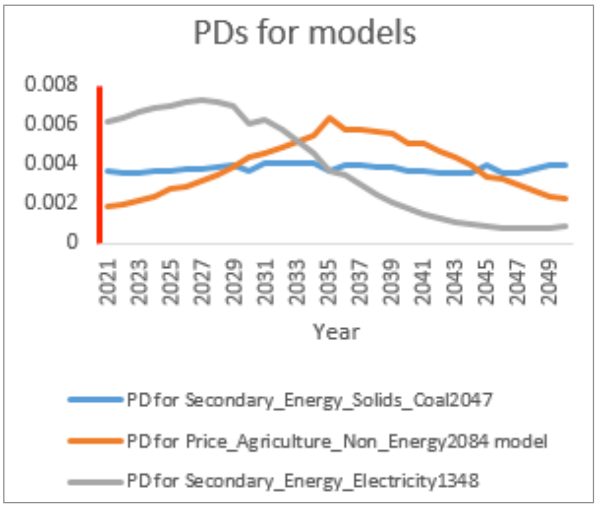
Table 7
Slope estimators in the auxiliary regression models and appropriate R-squared ratios for model variables

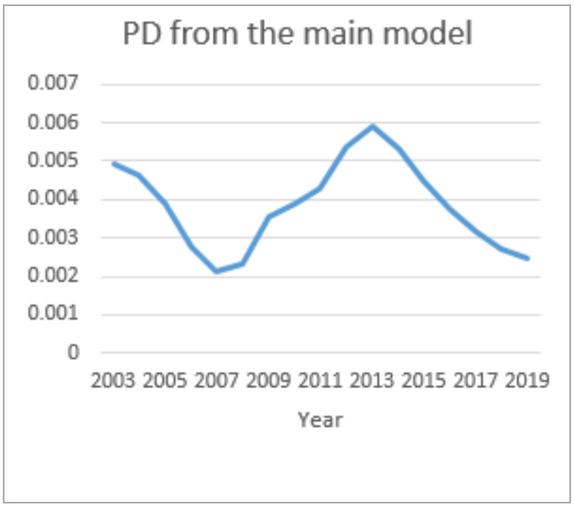
Variable	Scenario	
	Secondary_Energy_Electricity 1348	
	R^2	estimate
Model UR		
UNEMPLOYMENT_RATE	0.0847	29.501
ltv_current	0.1913	0.578
F_SAVINGS_3M	0.7882	-29971.600

Source: Authors' calculation

The Figure 8 shows the final PDs for the selected two scenarios. The results in the curves below present the purpose of the process of model building, which can give us an idea of future changes in the risk of the portfolio.

Figure 8
PDs predicted based on the assumed scenarios (left figure), PD from the main PD model (right figure)





Source: Authors' calculation

The PDs predicted by the scenario 'Price_Agriculture_Non_Energy2084' are more consistent with the latest PD values from the PD model (right curve) than for the scenario 'Secondary_Energy_Electricity1348'.

PDs for the scenario 'Secondary_Energy_Electricity1348' increases at the first stage until 2029 and decline faster than for the scenario 'Price_Agriculture_Non_Energy2084'. In conclusion, the behaviour of the PDs predicted based on the Disordered and Hot-house scenarios is consistent with business expectations.

Concluding the climate risk management in banks requires more attention. Our results indicate that banks should be concerned about climate risk management now and focus on climate risk management in the nearest future.

6. CONCLUSIONS

As discussed in this paper, the goal of this method is to define a simple approach that can be developed and implemented by institutions as a first attempt to climate risk stress tests management. In summary, in our research, we managed to use the NGFS data base in credit risk analysis and merge two different data sources: internal and external. We proposed a methodology for PD modelling using merged data sources. From PD logit model results we found that the main determinants predicting PD being correlated with NGFS scenarios are LTV, customer income, unemployment rate, and crude oil prices. The quality of the univariate models is above average, and the quality of the PD model is on average level. However, there are some weaknesses and inconsistencies as there is no explanation for some of the relationships between the NGFS scenarios and internal risk data, and big differences between forecasts for PD in different scenarios.

We would like highlight that works in banking sector should also focus on making improvements over the current approach, such as using Phase IV NGFS data. Phase III data from NGFS was used. Due to the release of Phase IV data from NGFS at the end of 2023, it is best to use the updated data. Additionally, new short-term scenarios from NGFS could be used. A dynamic balance sheet must be introduced for proper and reliable stress testing over a long-term horizon. Second round effects such as amplifiers and mitigants must be analysed and quantified. In further research we would also consider using a Bayesian approach in order to introduce prior information to the models. This could avoid overfitting, and would make models explainable. Those improvements should make the results of climate stress tests more reliable.

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Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and publication of the article.

Declaration about the scope of AI utilization

The authors did not use an AI tool in the preparation of the article.

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