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The Impact of Climate Risk on Credit Risk Parameters. Evidence from Five EU Economies

Abstract: Increasingly frequent extreme weather events, leading to rising climate risk, are one of the key aspects that financial institutions presently analyse. This paper highlights the connection between climate risk indicators and two main drivers of the traditional risk management process: default rates and loss rates. This information is valuable to financial institutions, enabling them to manage climate change risks more effectively. The study fills a scientific gap by using new indicators to analyse the impact of climate risk on credit risk in the largest EU economies. We show the results for the five biggest European Union economies (Germany, Spain, Italy, the Netherlands, and France). We demonstrate strong, moderate, and weak connections for each pair of climate risk drivers and risk parameters using three correlation measures: Pearson, Spearman, and Kendall-Tau. Significant differences are observed between countries, with the highest number of correlated variables in the Netherlands. A high correlation is also observed in France and Italy, while the correlations in Spain and Germany are less pronounced. The correlations also vary by asset class, highlighting the need for a case-by-case approach to climate risk assessment.

Keywords: credit risk, climate change, risk parameters, stress testing, climate risk

JEL: C51, C53, G18, Q54

1. Introduction

Environmental, social, and governance (ESG) risks increasingly influence global markets, posing significant financial stability and business resilience challenges. Their complex and interconnected nature demands proactive approaches to risk identification and mitigation. One risk that should be given special emphasis is the climate risk arising from the environmental factor. It stems from climate change, which is one of the greatest challenges of our time, both economically and in terms of socio-economic issues. Credit risk, defined as the potential loss resulting from the failure of a borrower to repay an obligation, is particularly relevant in the context of financial institutions. From the point of view of this type of entity, this risk is also associated with the non-receipt of capital due (which translates into a deterioration in cash flow) and an increase in collection costs (Kurniawan, Nurulrahmatia, Muniarty, 2024). In turn, the negative effects of climate risk can have a significant impact on the creditworthiness of borrowers, which consecutively affects their ability to repay their capital. In addition, climate risk drivers can affect the industry in different ways. Firstly, physical risks are associated with (i) long-term gradual climate change (e.g., sea level rise), (ii) extreme weather events (e.g., flooding), or (iii) indirect effects of climate change such as loss of ecosystem services (e.g., water scarcity). Secondly, transition risks are associated with the process of adapting to a low-carbon economy (Bank for International Settlements, 2021).

Growing interest in the interaction between the two risks has stimulated research in this area, which has shown that there is indeed a significant correlation between various indicators of climate risk and credit risk (Kleimeier, Viehs, 2016; Capasso, Gianfrante, Spinelli, 2020; Bell, van Vuuren, 2022). Thus, financial institutions and other financial market participants are facing climate change and need to manage those aspects as one of the highest regulated market sectors (see Australian Prudential Regulation Authority, 2021; Bank for International Settlements, 2021). This poses a challenge related to the revision of the methodology for stress testing exercises as one of the main tools for assessing the impact of external shocks on banks' solvency (Assouan, 2012). According to Baudino and Svoronos (2021), all these factors lead to a fundamental review of modelling techniques and stress testing methodologies, which can reduce their exposure to financial losses, reputational damage, and legal liability. However, due to a number of limitations (e.g., lack of standardised climate change data or difficulties in quantification), there are still many research gaps and opportunities to be explored. This study focuses on answering the question of the relationship between climate risk indicators and credit risk parameters in the five largest economies of the European Union. It uses data and indicators which, as far as we know, have not previously been used in a similar study.

In this paper, we explore a set of external factors to consider when identifying climate risks and a set of credit risk parameters, which are Probability of Default (PD) and Loss Given Default (LGD), for chosen European banking sectors (for Germany, Spain, Italy, the Netherlands, and France) from 2015 to 2024. These risk parameters are key inputs when assessing both Risk-Weighted Assets (RWA) to determine a financial institution's capital position. They also serve as a starting point for calculating provisions under International Financial Reporting Standards 9 (IFRS 9), which are a separate position in financial statements. Our ultimate contribution is to assess the properness and possible implications of climate risks on PD and LGD estimation. We highlight that choosing the most fitting design for climate risk modelling is crucial for adequate capital structure and provisioning, and all of these start with the risk drivers' selection.

The following study is an empirical analysis designed to examine various data groups connected with macroeconomic variables related to climate risk and industry trends. Each group is represented by a specific indicator: climate-related economic losses and the EU Eco-Innovation Index. In our study, climate-related economic losses represent physical risks while the EU Eco-Innovation Index embodies transition risks. For each variable belonging to the selected group, we calculate correlation measures and assess their suitability for further use in risk model calibration and, ultimately, in stress testing exercises. Such analysis can be beneficial in terms of meeting regulatory expectations, as financial institutions are expected to include climate and environmental risks as risk drivers in their risk management frameworks (European Central Bank, 2020). This means identifying and quantifying these risks as a part of the capital adequacy calculation process, which can be done by re-parametrisation of credit risk models by introducing newly defined variables into their structure. The current modelling framework assumes dependency of PD and LGD mainly on internal risk drivers (such as tenor, days past due, and collateral). However, these frameworks are not designed to include climate risk yet and need to be enhanced by new data related to climate change (Bank for International Settlements, 2020).

The structure of this article is as follows. Section 2 reviews the existing literature on climate risk. Section 3 explains the data regarding risk parameters and climate risk indicators. Section 4 illustrates the study and Section 5 concludes it.

2. Literature review

Over the years, society has become increasingly aware of the effects of climate change, which is why this topic is rightly attracting more and more attention, not only from researchers but also from the general public. These changes take a severe economic toll on the economies of many countries (Taha et al., 2024). They pose a danger not only to the stability of the financial system (U.S. Commodity Futures Trading Commission, 2020) but also to other various relevant areas such as public health (Haines et al., 2006), the supply chain (Godde et al., 2021) or Natural Resources Policy (Mendelsohn, 2009). They also have a negative impact on credit risk (Capasso, Gianfrante, Spinelli, 2020). Naturally, there is a need for measures of climate risks and empirical confirmation of whether there is a significant correlation between these risks and credit risk parameters. Subsequently, such climate risk measures may allow us to assess, mitigate, and prevent the negative effects of the resultant risks (Giglio, Kelly, Stroebel, 2021). The Paris Agreement is a significant development that we will refer to in this article. This is an international climate agreement concluded in 2015, and its main premise is to combat global warming by reducing it by at least 1.5°C (United Nations, 2015). We see this event as an external shock because it was the first major agreement among 196 countries with the only aim of addressing climate change and climate protection.

Credit risk is a one of the key factors in the stability of the financial system, affecting both banking decisions and the economic situation. The nature of this type of risk is reflected in the fact that it is the subject of much more research (compared with operational, market and liquidity risks) and the number of papers on it is constantly increasing. This, in turn, is reflected in the emergence of new tools and solutions for assessing and predicting credit risk (Barboza et al., 2016). The main credit risk models can be classified into structural and reduced form models. Structural models are based on the value of a company's assets and default thresholds derived from its balance sheet, while reduced-form models treat default as a random process without the need to observe the company's assets (Jarrow, Protter, 2012). Modern approaches to credit risk modelling combine classical elements with modern statistical methods or machine learning (Galindo, Tamayo, 2000).

As with credit risk, climate risk, if ignored or misjudged, can significantly disrupt the proper functioning not only of companies but also of the economy as a whole (Griffin, 2020). The first studies of climate risk began to appear in the 1980s and focused mainly on the issues regarding the prevention of pollution from large factories (EPCRA, 1986). In the early 21st century, studies linking air quality measures to corporate financial performance began to appear (Russo, Harrison, 2005). A common conclusion of early research on this phenomenon is that climate risk is material to a company's operations, regardless of stakeholder expectations or reputational aspects. In contrast, more recent research has broadened the scope to include accounting, financial reporting or legal proceedings, among others. It is also highlighted that there is still a lack of research focusing on the extent to which climate risk is reflected in asset value (Griffin, Sun, 2024).

As an essential part of the economy, financial institutions are also exposed to the adverse effects of climate risk. Losses caused by floods or earthquakes directly affect insurers. These phenomena also result in the loss of asset value of households and corporations, which in turn is reflected in the deterioration of the situation of banks that lend to the affected entities. The need to move towards a green economy may contribute to increased risks of economic dislocation and the emergence of 'stranded' assets (Campiglio et al., 2018). Although low carbon, these institutions have a significant environmental impact due to the huge size of the sector. This impact is mainly indirectly due to the financing of corporate activities, taking part in the assumption of risks, and brokering capital. In addition, financial institutions are increasingly selective when entering collaborations and favour entities engaged in sustainability (Zinczuk, Bolibok, Kasprzak-Czelej, 2023). Klimczak, Hadro, and Meyer (2023) have found that managers have significantly increased their focus on sustainability issues, including the environmental aspect, but their reports are overly positive and focus mainly on goals rather than outcomes, which in turn is one of the main reasons for criticism of the idea of sustainability data reporting. Nevertheless, there is a demand for sustainability reporting as it is the main source of knowledge for this type of qualitative data. Michalak

(2017) emphasises that non-financial information contained in company reports is often in the form of leading indicators and can serve as a valuation tool for investors and a source of data for forecasting.

Supervisors and policymakers are taking several actions to minimise the negative effects of climate change on the operations of financial institutions. This work is taking place at both national and international scales. The most important bodies responsible for climate regulation in the banking sector are the Basel Committee on Banking Supervision (BCBS) and the European Banking Authority (EBA). In addition, the EU policy on financial sector regulation focuses on addressing all ESG risks within the framework. At the moment, work is most advanced on environmental issues, but the other components of these risks (social and governance) will also be reflected in policy (Marcinkowska, 2022). Annual stress tests are one tool to assess the preparedness of banks to manage climate risk adequately, but for such tests to be carried out, climate risk data should be quantified (European Central Bank, 2020). The current studies have confirmed that both physical and transition risks are reflected in classical financial risks, including credit risk (Bank for International Settlements, 2021; Marcinkowska, 2023). Climate change can interact with credit risk through three factors: a borrower's cash flows, financial wealth, and type and value of the collateral, and all of them can affect the PD and LGD (Monnin, 2018).

There are studies in the existing literature on the impact of climate risk on credit risk, but it is not a widely developed area with research gaps and needs more exploration (Bell, van Vuuren, 2022). Current research confirms that climate change increases the default rate of companies (Capasso, Gianfrante, Spinelli, 2020; Bell, van Vuuren, 2022). Capasso, Gianfrante, and Spinelli (2020) used distance-to-default and carbon emissions to examine the impact of climate change on the credit risk of the companies included in the Bloomberg Barclays Agg Corporate Index. The results showed a negative association between these two variables, meaning that carbon-intensive companies are considered more likely to default. Kleimeier and Viehs (2016), studying UK publicly listed companies, have proven that higher carbon emissions significantly and negatively influence the cost of bank credit. Studies that directly analyse the impact of climate risk on PD and LGD risk factors with reference to banks are still lacking.

In our work, we use two selected indicators representing two factors to be considered when identifying climate risk. These indicators have been used in the climate or credit risk literature but not in the sense of the purpose of this study. Each represents a broader group of factors that can quantify climate risk, which is also relevant in the climate field and fills gaps in the literature.

Climate-related economic losses are a macroeconomic variable chosen as the first indicator of climate risk. There is no doubt that extreme weather conditions cause severe losses on many levels, which is the main reason why this indicator was chosen to represent a macroeconomic variable. They can cause direct economic losses occurring during or after the event (e.g., the value of flood-damaged buildings). Still, they can also cause indirect economic losses in the form of a decrease in added value (a reduction or even loss of revenue for a business due to the damage to the area caused by the earthquake and the inability of employees to reach it). In addition, direct and indirect effects are difficult to measure due to the delay in their quantification over time (Newman, Noy, 2023). Studies also show that much of this is attributed to climate change (IPCC, 2023). According to EEA (European Environment Agency, 2024), between 1980 and 2023, in the European Union, only the estimated costs generated by extreme weather events amounted to €738 billion, of which 22% relates to the years 2021–2023. In addition, no decrease in this trend is expected due to the observed increase in the occurrence of such events until 2030. There is no doubt that the economic impact of climate change needs to be taken into account and planned for, especially in vulnerable countries (Mochizuki et al., 2016). Concerning the banking sector, Nkwaira and van der Poll (2023) examined the relationship between economic damages and loan loss estimates of 40 major European banks. The results indicate that banks' knowledge in this area may be insufficient. The authors suggest that banks are overly cautious in estimating these losses to avoid deteriorating profitability. Furthermore, there is ample empirical evidence of the significant impact of climate change on banks' loan portfolios, and floods, extreme heat, and droughts have been identified as key factors (Aslan et al., 2022; Korzeb et al., 2024; Muzuva, Muzuva, 2024). Thus, it is recommended that banks include climate risk in their management system and practice sustainable lending practices by, among other things, financing green projects (Muzuva, Muzuva, 2024).

The second climate risk indicator – the EU Eco-Innovation Index – is representative of variable industry trends. Industry trends related to environmental issues strongly impact the actors that create the economic system, including the banking sector. The growing awareness of customers in these areas creates directions for activities as well as products and services offered, including banking products (Sia Partners, 2021). The main objective of introducing eco-innovations, also known in the literature as environmental or green, is to undertake activities that reduce environmental damage (in the form of pollution, energy, and resource consumption) compared to other available alternatives (Kemp, Pearson, 2008). The support of eco-friendly activities by banks can take place in some ways: financing green entities and organisations, reducing financing for brown industries, implementing green solutions in the financial services provided, or protecting natural resources (Dziawgo, 2014). The need to pay attention to eco-innovations was first highlighted in the Brundtland Report (Brundtland, 1987). Since then, companies have been increasingly involved in the issue of eco-innovations (Albitar, Al-Shaer, Liu, 2022), and the study of this topic and the development of such improvements is increasingly a subject of research and consideration (Schiederig, Tietze, Herstatt, 2012; Díaz-García, González-Moreno, Sáez-Martínez, 2015). In addition, studies are showing that the implementation of eco-innovations by companies brings many benefits on different levels (increased competitive advantage – Paulmoni et al., 2024; a positive impact on financial performance and better waste management – Albitar et al., 2024; the impact of green innovations on improving company performance – Kasraoui, Ben-Ahmed, Feidi, 2024). The choice of this indicator to represent industry trends was dictated by the fact that the implementation of eco-innovations is a response to increasing pressure from stakeholders regarding engagement with environmental issues (Nguyen, Adomako, 2021). Other indicators that may represent industry trends used in the literature include the Environmental Performance Index (EPI) (Schmidt-Traub et al., 2017) or the value of sustainable investment incurred (Global Sustainable

Investment Alliance, 2019). As for articles examining industry trends' impact on bank credit risk, here, too, there is a research gap that needs to be filled. Most studies focus on green innovations implemented by companies and their impact on aspects of operations. Safiullah, Phan, and Kabir (2024) studied US companies included in the ASSET4 database and the impact of green innovations on default risk (measured as distance-to-default, probability of default, and CDS spreads). The results confirmed that companies with higher levels of green innovation are less exposed to insolvency risk. In a study of Chinese banks, Yang and Masron (2024) have proven that digital transformation, one of the pillars of modern banking technology, significantly reduces credit risk in the form of defaulted loans.

3. Data

3.1. Risk parameters data

We acquire the data from the European Banking Authority (EBA) Risk Dashboard, which is a part of the regular Risk Assessment Report (European Banking Authority, n.d.). The EBA Risk Dashboard outlines the principal risks and vulnerabilities in the banking sector by assessing the evolution of key risk indicators, among which Default Rates and Loss Rates can be found. The data begins in Q1 2015, with each quarter reported to the most recent dates available. The report covers Internal Rating-Based (IRB) banks for two main asset classes: Corporate and Retail. The following breakdown is done by country of the counterparty (European Union (EU) and main non-EU countries). Besides weighted averages (by non-defaulted exposures for PDs and LGDs), the following stats are available: the number of observations, 25th percentile, 50th percentile, and 75th percentile.

We focus on default rates (DR) and loss rates (LR) which are calculated as follows:

$$DR = \frac{\text{Observed new defaults for the period}}{\text{Original exposure} - \text{Defaulted exposure}} = \frac{\sum_{i=0}^{3} \text{Obser.new defaults}_{Q-i}}{\frac{\sum_{i=0}^{3} \text{No defaulted exposures}_{Q-i}}{4}},$$

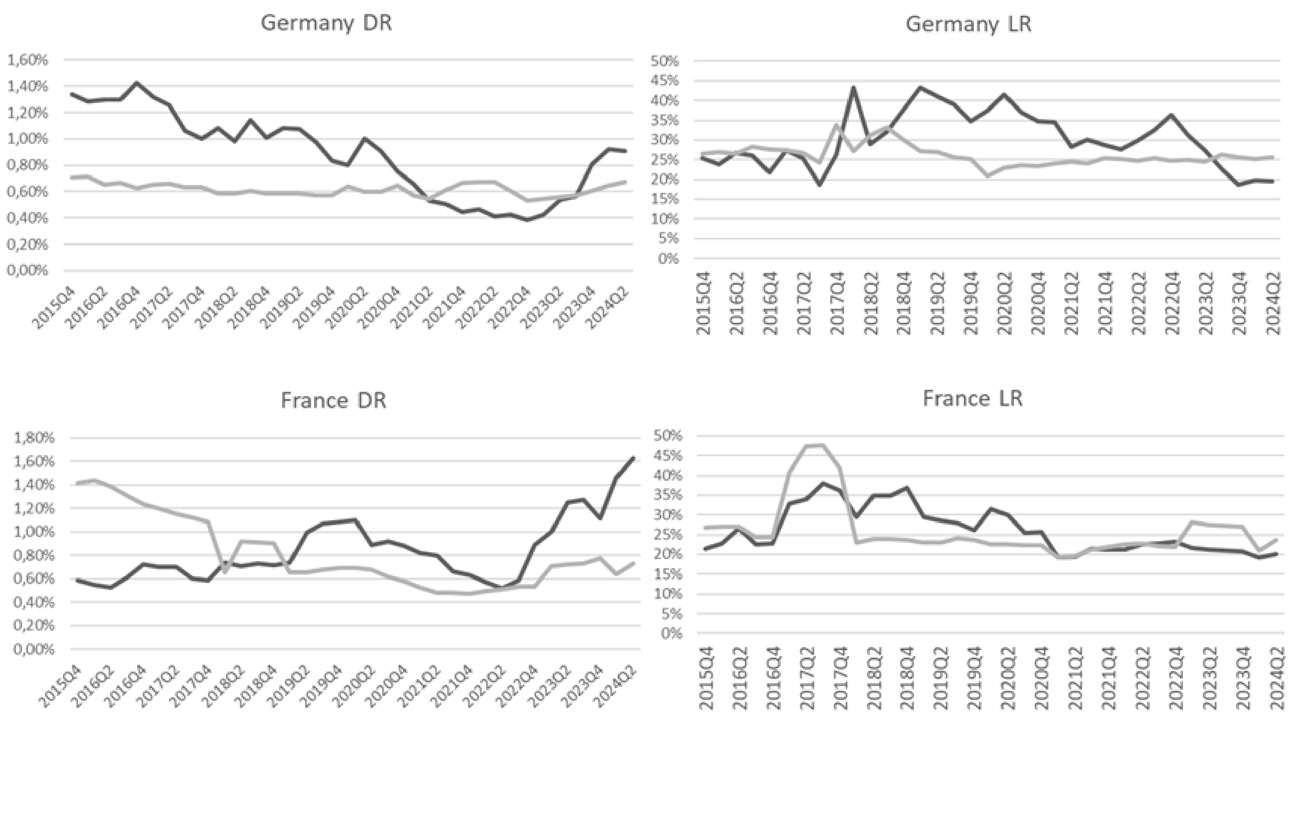
where the observed new defaults for the periods are the ones at the end of the period, and the defaulted exposures are the ones at the beginning of the period. The default rate is calculated on a yearly basis. The sum of the last four quarters is placed in the numerator. The average number of non-defaulted exposures of the last four quarters is in the denominator. $Q - i$ stands for the quarter expressed as a lag of the actual one. No defaulted exposures is calculated as a difference between "Original exposure and Defaulted exposure".

$$LR = \frac{\text{Credit risk adjustments (write-offs for observed new defaults)}}{\text{Observed new defaults for the period}} =$$

$$= \frac{\sum_{i=0}^{3} \text{"Credit risk adjustments"}_{Q-i}}{\sum_{i=0}^{3} \text{Obser.new defaults}_{Q-i}},$$

where the observed new defaults for the periods are the ones at the end of the period and $Q - i$ stands for the quarter expressed as a lag of the actual one.

As 39 countries are analysed in the Risk Dashboard, we decided to limit our study to the five largest economies in the EU to present transparent and meaningful results in a concise form. To select the proper ones, we used Gross Domestic Product (GDP) at market prices in 2023. According to the Eurostat Data Browser (Eurostat, 2025), these would be Germany, France, Italy, Spain, and the Netherlands. All these countries are part of the EBA reporting scope (for instance, sixth-placed Turkey is not). On the other hand, this selection covers a major part of the EU financial market (all ten banks with the largest assets are located in one of the five selected countries). We set our starting point as 2015Q4, the first date after adopting the Paris Agreement. We treat it as an external shock, which can significantly change the patterns in risk measured in terms of PD and LGD and climate in terms of variables described in the next section. Additionally, de Greiff, Delis, and Ongena (2018) have shown that banks did not price climate policy risk before 2015, but this risk became priced after the Paris Agreement. Figure 1 shows the default and loss rates trajectory for each selection divided by asset class.



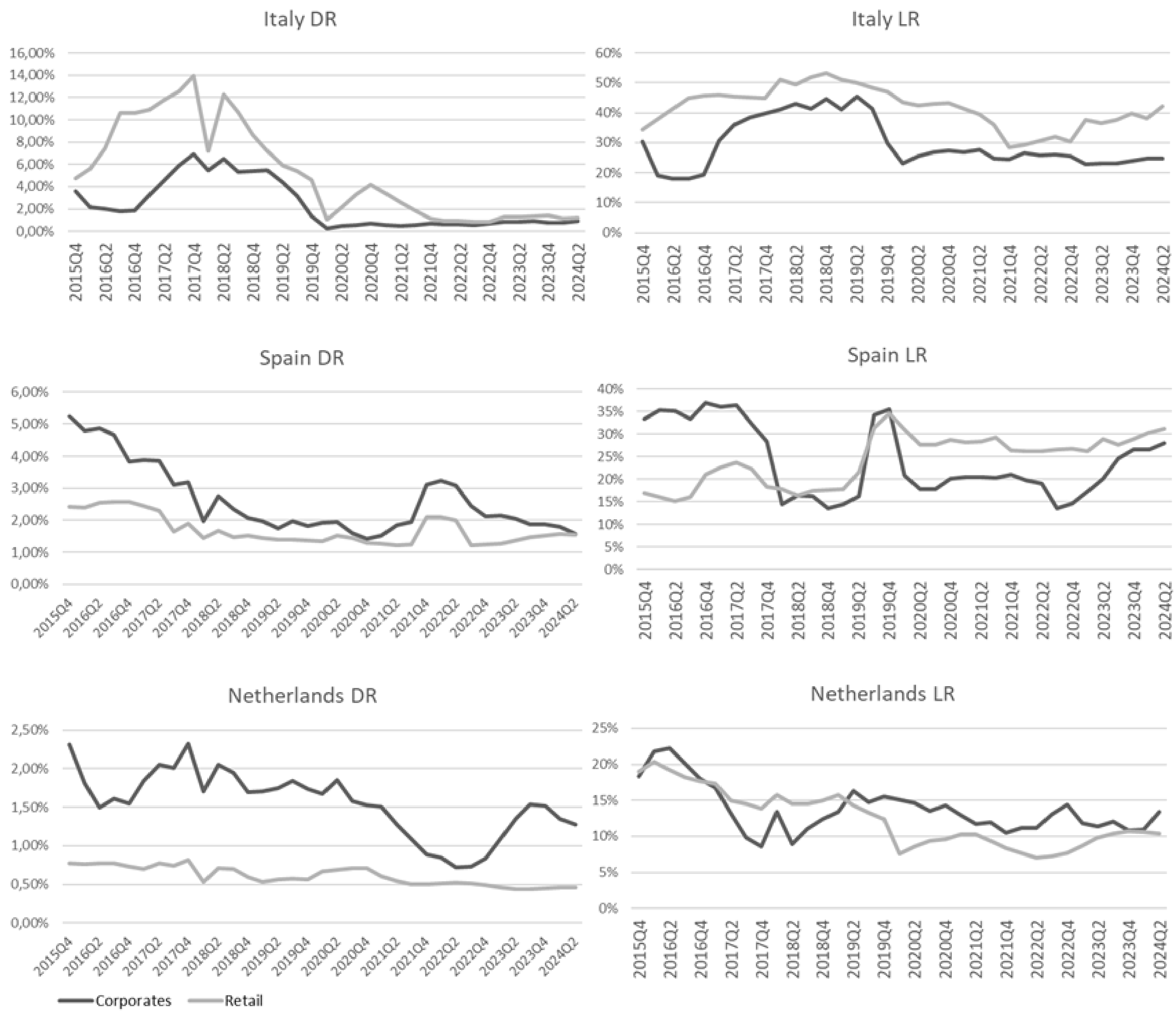


Figure 1. Default rates and loss rates divided by country and asset class

Source: own study based on the European Banking Authority (n.d.)

It can be clearly seen that each economy has its patterns, both in defaults and recoveries. The German market before 2020 had a default rate twice as high for corporate portfolios compared to the retail one. Then, during the COVID-19 pandemic, both lines showed an overlapping trend, which can be justified by government support for SMEs (European Commission, n.d.). Fiscal and monetary stimulus was also a reason for a default rate decrease from 2020Q1. Significant government help supported households and businesses and limited economic damage of the pandemic (*Default, Transition, and Recovery…*, 2021). However, starting from 2023Q4, the previous pattern returns. On the other hand, the loss ratio is primarily related to the bank's collection agenda, which can be focused on working with the clients to enhance the probability of cure (returning to working portfolio) or on quick sell exposures (keeping low Non-Performing Loans ratio). The broadly understood economy plays a supporting role in this context, as a higher unemployment rate (as an exemplary macroeconomic indicator) can influence the recovery pattern to some degree. We can state that the loss rate for the retail asset class is relatively stable over time, which can mean a well-structured debt collection process. For corporates, higher values are obtained between 2018Q2 and 2022Q4 on average.

Different trends are observed in France. The default rate for retail has been lower in recent years, starting from 1.42% in 2015Q4 to 0.73% in 2024Q2. The inverse pattern can be seen for corporates, where 0.55% was a starting value, but 1.63% can be observed in the last data point. As for now, the pattern in loss rates has not changed, as retail has experienced one uplift in 2017. However, besides this period, losses range from 19% to 29%. For corporates, recent data show lower losses than the previous ones (specifically 2017–2018).

For Italy, historical data before 2020 show a high magnitude of DR, which is connected not only to the cycle of crises in that market in the years 2014–2020 but also to the banking reform leading to the implementation of the Single Resolution Mechanism and the Single Resolution Fund within the framework of the Banking Union (Boccuzzi, 2022). After the crisis was managed, the default rate was similar to that in other countries. Loss rates for retail are constantly higher than for corporates, even if upturns and downturns show similar patterns. It should be stressed that the average level for the retail segment is higher than in any other county in the scope of the analysis. For the corporate asset class, only Germany has a higher average LR.

In the case of Spain, it can be seen that DR is gradually decreasing, reaching its minimum in 2021Q2. Then, especially in the case of corporate portfolios, some increase can be observed, but never as high as 5.23%, like in 2015Q4 (the maximum value). It can be associated with Spain's banking crisis of 2008–2014, which resulted from macro-financial imbalances and massive credit growth, mainly in the real estate sector (Baudino, Herrera, Restoy, 2023). This weakness was then managed by a series of reforms, impacting the following years. This could also be a reason for the high variability of loss rates in this market, as several collaterals in the form of real estate were put on the market simultaneously, which lowered prices in the years 2015–2017.

Finally, the Netherlands presents a relatively stable level of default rates compared to other countries. No major crisis was observed in this market, which can also be noticed regarding loss rates. Both retail and corporate asset classes show similar average levels of LR (12.41% vs 13.69%), which is rather low. It translates into a highly efficient collection process immune to downturn conditions.

Tables 1 and 2 present basic statistics for each country. For the retail asset class, the differences between regions are evident in default rates (the lowest in the Netherlands, the highest in Italy) and loss rates (the lowest again in the Netherlands, the highest again in Italy). The volatility, measured by standard deviation, shows slightly different results, where the German market achieved the lowest values for DR and LR. Conversely, Italy's DR and France's LR are the most volatile. A comparison of retail and corporate portfolios reveals another template. Besides Italy, corporate clients tend to default more frequently, achieving higher losses simultaneously. As SMEs are part of this sample, it is not unlikely to assess this portfolio as a riskier one.

Table 1. Summary statistics for default rates and loss rates – retail asset class [%]

Country	Mean	Standard deviation	Min	Max	Median
Germany DR	0.62	0.05	0.53	0.71	0.61
Germany LR	26.17	2.61	20.96	33.83	25.59
France DR	0.81	0.29	0.47	1.44	0.69
France LR	25.99	7.01	19.29	47.54	23.64
Italy DR	5.17	4.16	0.84	13.94	4.17
Italy LR	41.69	6.64	28.55	53.08	42.39
Spain DR	1.69	0.45	1.22	2.57	1.51
Spain LR	24.37	5.46	15.14	34.65	26.30
Netherlands DR	0.61	0.12	0.43	0.82	0.58
Netherlands LR	12.41	3.84	7.04	20.36	10.71

Source: own elaboration

Table 2. Summary statistics for default rates and loss rates – corporate asset class [%]

Country	Mean	Standard deviation	Min	Max	Median
Germany DR	0.88	0.31	0.39	1.43	0.92
Germany LR	30.27	6.97	18.56	43.21	29.06
France DR	0.84	0.27	0.52	1.63	0.74
France LR	26.07	5.67	19.09	37.94	23.17
Italy DR	2.31	2.09	0.23	6.90	0.91
Italy LR	29.45	8.09	18.04	45.43	26.68
Spain DR	2.62	1.06	1.42	5.23	2.06
Spain LR	23.91	7.89	13.54	37.03	20.49
Netherlands DR	1.55	0.41	0.72	2.32	1.58
Netherlands LR	13.69	3.27	8.55	22.21	13.19

Source: own elaboration

3.2. Climate risk indicators

In our study, we use two indicators that will measure climate risk at annual frequency. The time range chosen is from 2015 to 2024 and refers to the five economies we study: Germany, the Netherlands, Italy, France, and Spain.

Climate-related economic losses is an indicator published by Eurostat that measures economic statistics resulting from extreme weather and climate events. The unit of measurement is current prices in EUR. Data are provided by the European Environment Agency (EEA). Figure 2 shows how the values of economic losses due to climate events caused by climate change evolved between 2014 and 2023. This includes Germany, Spain, Italy, the Netherlands, and France. Each of these countries shows an increase in these values in each subsequent year. This is particularly evident in the case of Germany and Italy, where the value of losses has almost doubled in ten years.

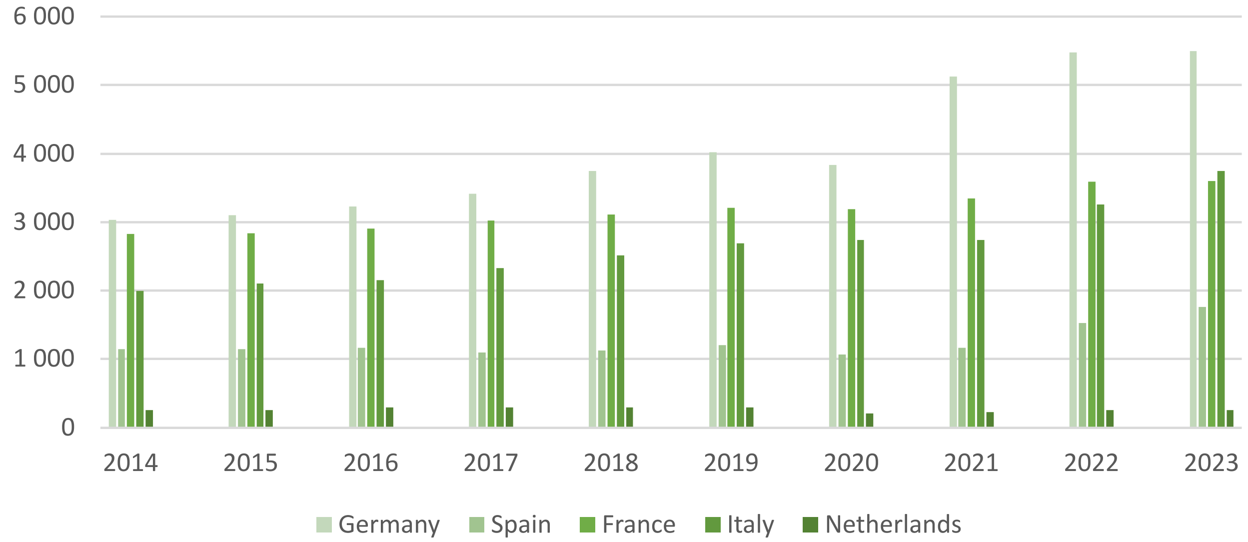


Figure 2. Economic losses (in million euro) caused by climate change for chosen countries

Source: own study based on data available in Eurostat (2024)

The EU Eco-Innovation Index is an indicator measuring the level of eco-innovation of the European Union Member States, indicating the ability of economies to develop and implement innovative environmental solutions. It is a composite indicator consisting of various measures made available by Eurostat, the OECD, and the EEA: eco-innovation inputs and outputs, eco-innovation activities, socio-economic performance, and resource efficiency performance. The index is measured as the average of the 12 indicators comprising the overall index. Figure 4 shows how the value of the achieved eco-innovation indexes for Germany, France, the Netherlands, Italy and Spain changed between 2013 and 2022. Here, as with the previous two indicators, a common upward trend is evident for all countries surveyed. This is due to the better results obtained by these countries in the relationship between innovation performance and new eco-innovation solutions.

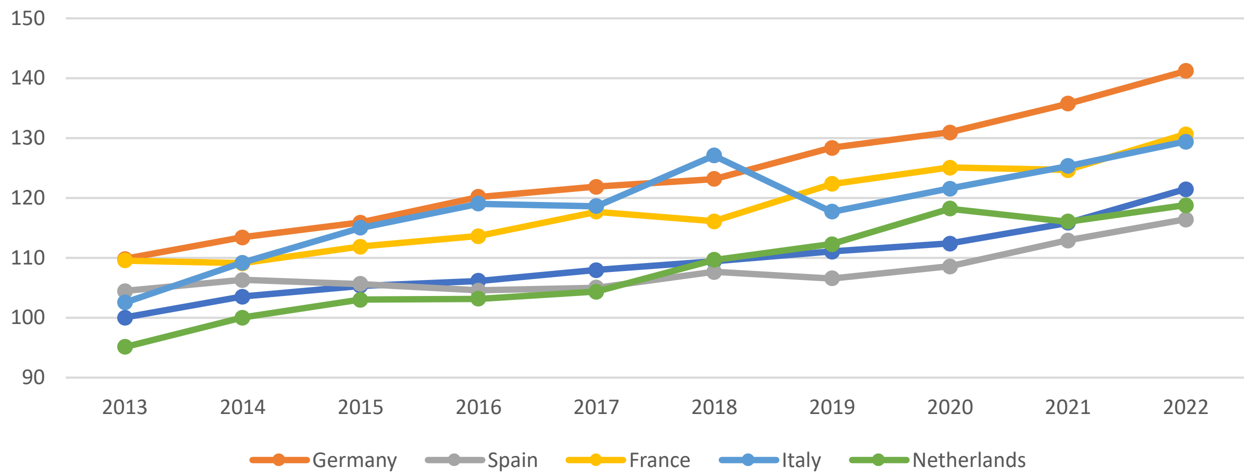


Figure 3. Eco-Innovation Index for chosen countries
Source: own study based on data available from the European Commission (2024)

4. Results

This study aims to determine how climate risk is linked to credit risk for banks in Germany, the Netherlands, Italy, Spain, and France. In this section, we assess the influence of climate risk indicators (represented by climate-related economic losses and the EU Eco-Innovation Index) on risk parameters (PD and LGD). Generally, we use the following strategy for each risk parameter vs climate risk indicator pair:

1. We prepared coherent time series covering the same period. Firstly, if one series was shorter than another, we cut it to the shorter one to avoid extrapolation error. Secondly, if there was an inconsistency in time series frequency, we always headed to the quarterly schema, as risk parameters are observed in such a snapshot. If there was a need to disaggregate, we used the Denton-Cholette method (Dagum, Cholette, 2006). In the case of aggregation, we used a simple average of more disaggregated time series.
2. We calculated lags for each climate risk indicator, a maximum of one year before the realisation of the selected risk parameter (so up to four lags). Such transformation is needed because climate change will not always affect default and loss rates instantaneously. As an example, transition risk realisation in the form of a change of policy regarding greenhouse gas emission will reveal its effect on the loan portfolio after the supply chain is modified, affecting the company's cash flows.
3. We then calculated correlation measures for each risk parameter (divided into country, asset class, and DR/LR). We chose this type of measure as it is commonly used in studies where a tool is needed to understand how one variable affects another. As a base indicator, we estimated the widely used Pearson coefficient (c.f. Mudelsee, 2003; Berthold, Höppner, 2016). We added Spearman's correlation coefficient (Ye et al., 2015) and Kendall's Tau (Hamed, 2009) to address possible non-linearities. For each correlation measure, we additionally calculated the p-value to assess the significance of each estimate. This choice provides

transparent and easy-to-follow results even if some drawbacks are inherent to these methods (such as the fact that correlation does not provide causation, which makes the fourth point crucial for the interpretation of the results).

4. Finally, we evaluated the economic sense of each estimate to determine if the direction of dependence follows the theoretical assumptions. We made the following expectations regarding analysed variables: a rise in Climate related economic losses should increase the default rate/loss rate, a rise in the Eco-Innovation Index should not increase the default rate/loss rate. We assess each indicator's usefulness based on the number of significant correlation coefficients. It means that each variable for each lag could be assessed as a strong one (three tests passed), a moderate one (two tests passed), a weak one (one test passed), or an insignificant (no tests passed). The results for each country are presented in a tabular form. Results that were not found to be statistically significant were excluded, but the full results are available from the authors on request.

In Table 3, we present the results for Germany. It is a leading economy in the European Union in terms of GDP (European Union, n.d.). We found a significant correlation between climate risk and default rates for the corporate asset class. The Eco-Innovation Index (lags 0–4) is characterised by a p-value below 5% cut-off, which means that these climate risk variables should be considered as risk drivers in the IFRS9/IRB infrastructures. Different patterns regarding default rates can be recognised for the retail asset class. Only a moderate relationship is valid for the Eco-Innovation Index (lag 3–4). A weak relationship is observed for Climate related economic losses (lag 4), and the Eco-Innovation Index (lags 0–2). Compared to the corporate asset class, there are only two moderate variables, with many weak ones. These limit the possibility of building robust models based on climate risk indicators and may suggest that another set should be sought. A weaker connection to the macroeconomic situation generally characterises the loss rates, as the recovery of assets can last even several years, sometimes during different economic regimes (cf. Qi, Yang, 2009; Yao, Crook, Andreeva, 2017). We could not find a strong or moderate relationship evidenced by two or three correlation coefficients concerning the corporate asset class. Only a weak one is associated with Climate related economic losses (lags 2–4). However, such a variable intuitively impacts loss rates connected with the deterioration of assets approved as collaterals. It makes Climate related economic losses a good point to start when modelling climate risk for this parameter. In the case of the retail asset class, the Eco-Innovation Index (lags 0–4) is marked as strong in our framework. No other variable meets the p-value condition, but a connection to climate risk is still more visible for the retail asset class than for the corporate one.

Table 3. Germany. Dimension distinguishes between: DR/CA – default rates for the corporate asset class, LR/CA – loss rates for the corporate asset class, DR/RA – default rates for the retail asset class, LR/RA – loss rates for the retail asset class [%].

Dimension	Variable	Lag	Pearson	p-val	Spearman	p-val	Kendall-Tau	p-val
DR/CA	Climate related economic losses	No significant correlation with expected sign						
DR/CA	Eco-Innovation Index	0	**– 89.21**	**0.00**	**– 92.40**	**0.00**	**– 78.18**	**0.00**
		1	**– 88.18**	**0.00**	**– 91.80**	**0.00**	**– 76.03**	**0.00**
		2	**– 87.73**	**0.00**	**– 91.34**	**0.00**	**– 75.32**	**0.00**
		3	**– 87.67**	**0.00**	**– 90.99**	**0.00**	**– 73.96**	**0.00**
		4	**– 88.12**	**0.00**	**– 90.71**	**0.00**	**– 73.12**	**0.00**
DR/RA	Climate related economic losses	0	– 2.89	87.30	– 38.54	2.68	– 27.11	2.67
		1	– 3.81	83.59	– 40.99	1.98	– 29.26	1.87
		2	– 8.26	65.88	– 39.58	2.75	– 28.42	2.48
		3	– 16.53	38.28	– 37.38	4.19	– 27.16	3.52
		4	– 26.32	16.77	– 32.98	8.06	**– 26.39**	**4.47**
DR/RA	Eco-Innovation Index	0	– 20.09	29.61	– 36.73	5.00	**– 31.81**	**1.55**
		1	– 16.33	40.64	– 31.75	9.97	**– 28.34**	**3.45**
		2	– 18.83	34.70	– 32.12	10.24	**– 29.67**	**3.01**
		3	– 28.00	16.60	**– 44.90**	**2.14**	**– 40.06**	**0.42**
		4	– 38.55	5.70	**– 59.40**	**0.17**	**– 50.42**	**0.04**
LR/CA	Climate related economic losses	0	– 3.10	86.40	19.29	28.22	8.15	50.52
		1	6.57	72.09	30.24	9.25	14.73	23.64
		2	14.77	42.77	**40.10**	**2.54**	20.67	10.27
		3	20.35	28.07	**39.60**	**3.03**	21.17	10.07
		4	23.53	21.91	**36.73**	**5.00**	18.99	14.86
LR/CA	Eco-Innovation Index	No significant correlation with expected sign						
LR/RA	Climate related economic losses	No significant correlation with expected sign						
LR/RA	Eco-Innovation Index	0	**– 52.11**	**0.37**	**– 59.79**	**0.06**	**– 35.76**	**0.65**
		1	**– 51.07**	**0.55**	**– 61.09**	**0.06**	**– 36.29**	**0.68**
		2	**– 50.72**	**0.69**	**– 60.02**	**0.09**	**– 37.09**	**0.67**
		3	**– 49.02**	**1.10**	**– 59.67**	**0.13**	**– 36.98**	**0.82**
		4	**– 48.70**	**1.35**	**– 59.01**	**0.19**	**– 37.06**	**0.95**

Note: Relations with expected signs and statistically significant p-value are in bold

Source: own elaboration

In Table 4, we show the results for France. In terms of corporate default rates, there is no variable for which all three correlation measures are significant. France's patterns in the case of defaulting are not correlated strongly with economic indicators, even when lags are considered. It may be too early to include climate risk variables in the modelling framework, as incorporating new risk drivers should not materially decrease the overall performance of the rating system (European Banking Authority, 2023). Opposite remarks can be made for the retail asset class. The Eco-Innovation Index is highly correlated for all considered lags. Climate-related economic losses are out of scope due to unintuitive signs of correlation, which implies lower default rates when climate-related economic losses increase. In summary, one variable (but for all lags) is significant for climate risk identification in credit risk modelling. In the case of loss rates for the corporate asset class, a strong connection between variables is found only for the Eco-Innovation Index (lags 2–4). A weak one is reported for the Eco-Innovation Index (lags 0–1). Again, like for retail default rates, the Climate related economic losses variable is not included in the final list. However, the Eco-Innovation Index should be considered as an initial set of information-enhancing PD and LGD data sets. The last analysis for France covers loss rates for the retail asset class. We can distinguish a strong relationship with the Eco-Innovation Index (lags 0–4). These imply that the Climate related economic losses variable is not connected to any parameter regarding default and loss rates for the corporate and retail asset classes. In France's case, the Eco-Innovation Index variable plays a major role in climate risk identification.

Table 4. France. Dimension distinguishes between: DR/CA – default rates for the corporate asset class, LR/CA – loss rates for the corporate asset class, DR/RA – default rates for the retail asset class, LR/RA – loss rates for the retail asset class [%].

Dimension	Variable	Lag	Pearson	p-val	Spearman	p-val	Kendall-Tau	p-val
DR/CA	Climate related economic losses	No significant correlation with expected sign						
DR/CA	Eco-Innovation Index	No significant correlation with expected sign						
DR/RA	Climate related economic losses	No significant correlation with expected sign						
DR/RA	Eco-Innovation Index	0	**–83.81**	**0.00**	**–85.48**	**0.00**	**–65.35**	**0.00**
		1	**–83.77**	**0.00**	**–84.66**	**0.00**	**–64.37**	**0.00**
		2	**–83.21**	**0.00**	**–81.30**	**0.00**	**–62.20**	**0.00**
		3	**–82.12**	**0.00**	**–77.83**	**0.00**	**–59.78**	**0.00**
		4	**–81.26**	**0.00**	**–77.25**	**0.00**	**–60.43**	**0.00**
LR/CA	Climate related economic losses	No significant correlation with expected sign						

Dimension	Variable	Lag	Pearson	p-val	Spearman	p-val	Kendall-Tau	p-val
LR/CA	Eco-Innovation Index	0	**– 37.36**	**4.59**	– 28.62	13.22	– 19.98	12.86
		1	**– 38.14**	**4.52**	– 31.94	9.75	– 20.40	12.81
		2	**– 40.49**	**3.62**	**– 41.12**	**3.31**	**– 27.39**	**4.53**
		3	**– 42.40**	**3.09**	**– 47.87**	**1.34**	**– 33.28**	**1.73**
		4	**– 40.46**	**4.49**	**– 44.78**	**2.48**	**– 31.05**	**2.98**
LR/RA	Climate related economic losses	No significant correlation with expected sign						
LR/RA	Eco-Innovation Index	0	**– 37.91**	**4.26**	**– 73.36**	**0.00**	**– 50.55**	**0.01**
		1	**– 42.68**	**2.35**	**– 72.29**	**0.00**	**– 49.01**	**0.03**
		2	**– 52.02**	**0.54**	**– 74.89**	**0.00**	**– 53.07**	**0.01**
		3	**– 62.53**	**0.06**	**– 82.48**	**0.00**	**– 61.02**	**0.00**
		4	**– 68.98**	**0.01**	**– 87.48**	**0.00**	**– 68.45**	**0.00**

Note: Relations with expected signs and statistically significant p-value are in bold

Source: own elaboration

As for previous countries, Italy's analysis starts with corporate asset class default rates (Table 5). Similarly to France, the Eco-Innovation Index is strongly connected but only for lag 4. It could suggest that there is no instant effect of introducing eco-innovations on defaulting patterns in this case. The Climate related economic losses variable could not be perceived as having a moderate or weak relationship with the analysed risk parameter. Only slightly different results are obtained for the retail asset class when it comes to default rates. Climate related economic losses again drive the considered variable in the opposite direction, as economic intuition suggests. A different pattern is found for the Eco-Innovation Index, where the strongest match is achieved for a variable with no lag. Lags from 1 to 3 have a moderate impact, with lag 4 having only a weak connection. Based on these results, we can state that for the retail asset class, the impact of the Eco-Innovation Index starts instantly and weakens over time. Italy's loss rates for the corporate asset class are the second risk parameter, where no connection to the climate risk indicators could be established. Moreover, only the Eco-Innovation Index correlation coefficients have an intuitive direction. In such a case, we suggest enhancing the climate risk indicators dataset to introduce a wider range of variables. Heatwave frequency, sea surface temperature, or investments in sustainable development can be perceived as country-specific variables that can be analysed individually for Italy. Loss rates for the retail asset class had a strong impact on the Eco-Innovation Index (lags 1–4). A moderate impact can be reported for the Eco-Innovation Index with no lags. This situation is similar to France's case, where Climate related economic losses were not introduced in any dimension into the list of correlated variables.

Table 5. Italy. Dimension distinguishes between: DR/CA – default rates for the corporate asset class, LR/CA – loss rates for the corporate asset class, DR/RA – default rates for the retail asset class, LR/RA – loss rates for the retail asset class [%].

Dimension	Variable	Lag	Pearson	p-val	Spearman	p-val	Kendall-Tau	p-val
DR/CA	Climate related economic losses	No significant correlation with expected sign						
DR/CA	Eco-Innovation Index	0	– 16.98	37.86	– 21.95	25.26	– 12.58	33.87
		1	– 18.83	33.72	– 25.40	19.21	– 16.16	22.81
		2	– 22.29	26.37	– 26.77	17.69	– 15.98	24.29
		3	– 30.18	13.41	– 33.37	9.57	– 22.19	11.24
		4	**– 42.14**	**3.59**	**– 43.97**	**2.79**	**– 30.38**	**3.35**
DR/RA	Climate related economic losses	No significant correlation with expected sign						
DR/RA	Eco-Innovation Index	0	**– 36.76**	**4.98**	**– 43.92**	**1.71**	**– 32.80**	**1.26**
		1	– 36.10	5.91	**– 44.01**	**1.91**	**– 33.11**	**1.35**
		2	– 35.79	6.68	**– 41.49**	**3.14**	**– 31.95**	**1.95**
		3	– 35.10	7.87	**– 39.53**	**4.56**	**– 30.82**	**2.75**
		4	– 33.04	10.68	– 37.35	6.59	**– 31.72**	**2.65**
LR/CA	Climate related economic losses	No significant correlation with expected sign						
LR/CA	Eco-Innovation Index	No significant correlation with expected sign						
LR/RA	Climate related economic losses	No significant correlation with expected sign						
LR/RA	Eco-Innovation Index	0	**– 41.29**	**2.60**	– 36.48	5.17	**– 30.83**	**1.90**
		1	**– 49.44**	**0.75**	**– 46.64**	**1.24**	**– 35.23**	**0.86**
		2	**– 55.41**	**0.27**	**– 52.79**	**0.47**	**– 39.37**	**0.40**
		3	**– 54.80**	**0.38**	**– 51.56**	**0.70**	**– 41.29**	**0.31**
		4	**– 47.27**	**1.70**	**– 45.28**	**2.30**	**– 38.40**	**0.72**

Note: Relations with expected signs and statistically significant p-value are in bold

Source: own elaboration

In Table 6, we present the results for Spain, first for default rates and then for loss rates. The Eco-Innovation Index (lags 2–4) reflects the strongest connections with default rates for the corporate asset class. A moderate impact is valid for the Eco-Innovation Index (lag 0–1). Climate-related economic losses are not significant for any lag or correlation measure.

The retail asset class in terms of default rates has the most substantial connection with the Eco-Innovation Index (lags 3–4). A medium correlation is found for the Eco-Innovation Index (lags 0–2). It creates the same pattern as the one recognised in the corporate asset class, where the Climate related economic losses variable was not introduced into the final list. However, the Eco-Innovation Index represents the climate risk reflection in default rates well. Moving to the second risk parameter for Spain, we can distinguish a strong relationship between the Eco-Innovation Index (lags 0–1). Only a weak correlation is found, represented by the Eco-Innovation Index (lags 2–3). These sets still can serve as a starting point for more advanced analysis, covering modelling techniques. The last analysis for Spain covers loss rates for the retail asset class. In this case we did not find any significant relationship. We can distinguish two reasons for this. Firstly, the relation acts in the opposite direction than intended, like in case of the Eco-Innovation Index, where higher values of the index are positively correlated with loss rates. Secondly, the correlation is not significant, like in the case of Climate related economic losses (for example, lag 4, where the direction is expected, but not strong enough). In this case, the next step could be including more country specific variables, such as heat risk, desertification, or pollution from industrial livestock farming.

Table 6. Spain. Dimension distinguishes between: DR/CA – default rates for the corporate asset class, LR/CA – loss rates for the corporate asset class, DR/RA – default rates for the retail asset class, LR/RA – loss rates for the retail asset class [%].

Dimension	Variable	Lag	Pearson	p-val	Spearman	p-val	Kendall-Tau	p-val
DR/CA	Climate related economic losses	No significant correlation with expected sign						
DR/CA	Eco-Innovation Index	0	– 32.43	8.61	**– 49.19**	**0.67**	**– 29.35**	**2.56**
		1	– 35.93	6.04	**– 53.21**	**0.36**	**– 33.11**	**1.35**
		2	**– 41.66**	**3.06**	**– 59.04**	**0.12**	**– 39.94**	**0.35**
		3	**– 51.38**	**0.73**	**– 64.46**	**0.04**	**– 44.99**	**0.13**
		4	**– 62.14**	**0.09**	**– 72.94**	**0.00**	**– 53.09**	**0.02**
DR/RA	Climate related economic losses	No significant correlation with expected sign						
DR/RA	Eco-Innovation Index	0	– 33.14	7.90	**– 62.45**	**0.03**	**– 46.61**	**0.04**
		1	– 33.81	7.85	**– 62.52**	**0.04**	**– 48.48**	**0.03**
		2	– 34.52	7.78	**– 60.14**	**0.09**	**– 44.51**	**0.11**
		3	**– 45.02**	**2.10**	**– 67.33**	**0.02**	**– 49.92**	**0.04**
		4	**– 56.80**	**0.31**	**– 74.78**	**0.00**	**– 55.09**	**0.01**

Dimension	Variable	Lag	Pearson	p-val	Spearman	p-val	Kendall-Tau	p-val
LR/CA	Climate related economic losses	No significant correlation with expected sign						
LR/CA	Eco-Innovation Index	0	**– 62.36**	**0.03**	**– 66.44**	**0.01**	**– 44.64**	**0.07**
		1	**– 57.59**	**0.13**	**– 55.84**	**0.20**	**– 35.23**	**0.86**
		2	**– 49.69**	**0.84**	– 38.04	5.03	– 20.54	13.33
		3	**– 44.13**	**2.40**	– 27.66	17.13	– 14.79	28.99
		4	– 39.16	5.29	– 21.16	31.00	– 11.02	44.08
LR/RA	Climate related economic losses	No significant correlation with expected sign						
LR/RA	Eco-Innovation Index	No significant correlation with expected sign						

Note: Relations with expected signs and statistically significant p-value are in bold

Source: own elaboration

In Table 7, we present the results for the Netherlands, first for default rates and then for loss rates. Regarding the corporate asset class in terms of default rate, the Netherlands is the first country to find all climate risk indicators strongly correlated with this risk parameter. It is also the first time a strong connection with climate-related economic losses can be reported (previously, only a moderate or weak connection was found for Germany). This connection can be explained by relatively stable markets, as described in the 'Risk Parameters Data' section. Nevertheless, the influence of climate risk on the Netherlands default rates can be assessed by econometric models with a high probability of achieving statistically significant estimates. Similar conclusions can be made regarding retail asset class default rates. Again, all climate risk indicators are characterised by a strong relationship with the risk parameter analysed. Also, all of them work in an assumed direction, especially for Climate related economic losses, which was not always true for previously analysed countries. We can sum up that default rates in the case of the Netherlands are strongly correlated with climate risk indicators, which made them suitable for modelling in either IFRS 9 or IRB regimes. In the case of corporate loss rates, we can observe different patterns. Similarly to France, Italy and Spain, Climate related economic losses are not well correlated with selected risk parameters. However, we can select one strong variable from the rest of the set: the Eco-Innovation Index (lag 2). A moderate correlation is found for the Eco-Innovation Index (lags 1, 3 and 4). Finally, weak relations are assessed in the Eco-Innovation Index (lag 0). This can lead to the conclusion that loss rates are effectively harder to correlate with macroeconomic indices, both for standard variables such as GDP or unemployment rate and climate risk indicators. What was hard to assess for the corporate asset class is highly visible for the retail asset class in terms of loss rates. Like default rates, all climate risk indicators are significant regarding the Pearson, Spearman, and Kendall-Tau coefficients. It is particularly important for Climate related economic losses, whose correlation with loss rates can be easily introduced into risk models as the one with the highest intuitiveness, as mentioned before. Overall, the Netherlands can be perceived as a country where initial analysis regarding climate impact on risk parameters can end with high predictive power models, forecasting future losses through PD and LGD parameters.

Table 7. Netherlands. Dimension distinguishes between: DR/CA – default rates for the corporate asset class, LR/CA – loss rates for the corporate asset class, DR/RA – default rates for the retail asset class, LR/RA – loss rates for the retail asset class [%].

Dimension	Variable	Lag	Pearson	p-val	Spearman	p-val	Kendall--Tau	p-val
DR/CA	Climate related economic losses	0	**59.56**	**0.03**	**63.56**	**0.01**	**37.73**	**0.20**
		1	**63.79**	**0.01**	**57.24**	**0.06**	**31.69**	**1.09**
		2	**62.06**	**0.02**	**53.69**	**0.18**	**31.43**	**1.31**
		3	**55.55**	**0.14**	**53.18**	**0.25**	**35.90**	**0.54**
		4	**45.96**	**1.21**	**50.92**	**0.48**	**37.73**	**0.41**
DR/CA	Eco--Innovation Index	0	**– 75.13**	**0.00**	**– 71.56**	**0.00**	**– 51.54**	**0.01**
		1	**– 72.33**	**0.00**	**– 69.03**	**0.00**	**– 51.66**	**0.01**
		2	**– 65.93**	**0.02**	**– 63.68**	**0.04**	**– 47.93**	**0.05**
		3	**– 56.65**	**0.26**	**– 55.26**	**0.34**	**– 40.06**	**0.42**
		4	**– 46.49**	**1.92**	**– 44.35**	**2.64**	**– 29.05**	**4.21**
DR/RA	Climate related economic losses	0	**48.45**	**0.43**	**54.63**	**0.10**	**35.83**	**0.34**
		1	**60.77**	**0.02**	**58.60**	**0.04**	**40.16**	**0.12**
		2	**68.16**	**0.00**	**60.15**	**0.03**	**43.92**	**0.05**
		3	**70.25**	**0.00**	**59.76**	**0.05**	**41.43**	**0.13**
		4	**67.54**	**0.01**	**62.10**	**0.03**	**45.13**	**0.06**
DR/RA	Eco--Innovation Index	0	**– 76.28**	**0.00**	**– 77.18**	**0.00**	**– 56.97**	**0.00**
		1	**– 78.85**	**0.00**	**– 83.59**	**0.00**	**– 62.78**	**0.00**
		2	**– 79.34**	**0.00**	**– 85.42**	**0.00**	**– 65.62**	**0.00**
		3	**– 76.41**	**0.00**	**– 82.48**	**0.00**	**– 61.63**	**0.00**
		4	**– 70.35**	**0.01**	**– 75.36**	**0.00**	**– 56.43**	**0.01**
LR/CA	Climate related economic losses	No significant correlation with expected sign						
LR/CA	Eco--Innovation Index	0	**– 43.00**	**1.99**	– 32.69	8.35	– 19.98	12.86
		1	**– 49.42**	**0.75**	**– 37.44**	**4.96**	– 24.64	6.61
		2	**– 53.84**	**0.38**	**– 39.93**	**3.91**	**– 27.39**	**4.53**
		3	**– 55.47**	**0.33**	**– 38.50**	**5.21**	– 23.42	9.38
		4	**– 56.80**	**0.31**	**– 41.89**	**3.71**	– 26.38	6.50

Dimension	Variable	Lag	Pearson	p-val	Spearman	p-val	Kendall-Tau	p-val
LR/RA	Climate related economic losses	0	**70.98**	**0.00**	**70.61**	**0.00**	**45.69**	**0.02**
		1	**74.88**	**0.00**	**73.16**	**0.00**	**48.64**	**0.01**
		2	**72.28**	**0.00**	**73.37**	**0.00**	**49.95**	**0.01**
		3	**64.69**	**0.01**	**69.06**	**0.00**	**45.57**	**0.04**
		4	**54.26**	**0.24**	**60.57**	**0.05**	**40.20**	**0.22**
LR/RA	Eco-Innovation Index	0	**– 93.62**	**0.00**	**– 92.15**	**0.00**	**– 74.72**	**0.00**
		1	**– 94.10**	**0.00**	**– 94.43**	**0.00**	**– 80.26**	**0.00**
		2	**– 92.49**	**0.00**	**– 93.36**	**0.00**	**– 80.46**	**0.00**
		3	**– 88.86**	**0.00**	**– 87.13**	**0.00**	**– 69.65**	**0.00**
		4	**– 83.72**	**0.00**	**– 79.59**	**0.00**	**– 61.77**	**0.00**

Note: Relations with expected signs and statistically significant p-value are in bold

Source: own elaboration

Taking it all into consideration, we can make the following remarks which can be particularly important for future research as well as for risk managers when it comes to directions in which risk models development should go in the future. Also, regulatory bodies can introduce an initial set of variables which should be taken into account when climate risk is analysed. To sum up:

1. There is no consistency regarding a set of climate risk indicators between countries. The highest level of correlation for the German market was achieved for the Eco-Innovation Index. Also in Spain, the situation looked similar to Germany. Finally, for the Netherlands, both variables were correlated significantly to some risk parameters, especially Climate related economic losses.
2. Differences between loss rates and default rates are the most visible regarding correlated variables. Loss rates generally achieved less significant results, as fewer variables showed statistically confirmed evidence of dependence. Despite that fact, no clear pattern exists between variables correlated to default rates and loss rates. Depending on the portfolio, specific indicators were used. The Eco-Innovation Index can be perceived as one generally valid across risk parameters and asset classes.
3. No connection with climate risk indicators could be found for some risk parameters and asset classes. It creates a need for further analysis of country-specific risk drivers. Each economy and its banking system can be vulnerable to some sector-specific risks. Additionally, transition risk depends highly on each country's judicial effectiveness and the behaviour of economic actors and policymakers. Even if calculated at a country level, EU-wide variables can be a good starting point for finding more sophisticated dependencies.
4. In connection with point three, further research should focus on building basic and eventually more advanced econometric models, taking into consideration the analysis of risk drivers performed in this paper. It can consist of time-series modelling with the use of the data from the Risk Assessment Report, but we encourage the use of internal financial institution data

to check the vulnerability of the banking sector on a micro level. Finally, such an analysis can also be performed on the client/contract level to produce a new component of PD/LGD models dedicated to climate risk assessment.

5. Conclusions

In recent years, central banks, regulators and financial institutions have become increasingly interested in understanding the impact of climate risks on financial stability. Moreover, the banking sector plays a large role in managing the negative impacts of climate change. Integrating climate risks into the management framework is quite a challenge for banks but their implementation is essential on the road to CO_2 neutrality. Also, the Paris Agreement imposes risks on carbon-intensive companies. Existing environmental regulations may not be conservative enough to prevent climate change, which may ultimately lead to an increase in unexpected losses that need to be covered by regulatory capital (mainly through RWA).

The main research question of this paper is whether currently maintained climate risk indicators correlate with risk parameters to such an extent that robust models can be built to predict future climate-related losses. Given the specificity of this type of information and the lack of a standardised framework for its reporting, it is necessary to prove which of the selected indicators are appropriate. These results provide important information on the practical use of climate risk indicators. We contribute to this strand of literature by investigating whether climate-related economic losses and eco-innovation rates affect default and loss rates. Our analysis was conducted for the five largest EU countries in terms of GDP (Germany, France, Italy, Spain, and the Netherlands).

We find that climate risk indicators correlate significantly with risk parameters in almost all dimensions (two risk parameters times two asset classes times five countries). Only three parameter/asset class pairs out of 20 combinations are not correlated with any climate risk indicator (France DR for corporates, Italy LR for corporates and Spain LR for retail). In addition, our results show high variability regarding the importance of climate risk indicators for each country and even for given risk parameters. It means that each country deserves a dedicated analysis, not only at the risk parameter level but also at the asset class level. Turning to the drivers of the risk estimates, we find strong evidence that the Eco-Innovation Index impacts the default rate and loss rate in the largest number of dimensions (72% of combinations). Moreover, the Netherlands is the country where most of the indicators showed a significant correlation (84% correlated combinations and 69% with a strong correlation). A strong correlation was found for all climate indicators for the default rate (both corporate and retail) and for the loss rate in the retail asset class. Only for the corporate loss rates there were combinations that showed moderate, weak or no correlation. The highest number of strong correlations was found for the Netherlands (88% of all correlated observations, of which 78% were strongly correlated). This was followed by Germany (40% of combinations correlated; 25% with a strong correlation), France (38% of combinations correlated and 33% strongly correlated), and Spain (35% correlated and 18% strongly correlated). These outcomes confirm that sustainability-related product offerings, transition finance policies, loan origination policies or ESG-related targets and limits will impact the financial results of the banking sector, as climate risk introduction into risk modelling will disturb the results in a short- and long-term perspective. Even smaller institutions are not immune to climate risk (for example, via the concentration of exposures in ESG-sensitive economic sectors), so currently maintained portfolios are influenced by this kind of hazard. Our results are in line with present knowledge about management and measurement of climate risk (cf. European Banking Authority, 2025). From the theoretical point of view, the most surprising result is the lack of significance for Climate-related economic losses in many dimensions. It could be argued that such losses are still not present in the balance sheets of financial institutions to a sufficient extent, even if we shorten the analysed period to 2015.

We initially attempted to include the impact of environmental taxes as a regulatory indicator in the study of the impact of climate policy, but due to the controversial nature of these taxes, the volatility of the correlations obtained from the analyses – especially in the case of transport taxes – and the divergent interpretations of their impact on the economy, we decided to exclude them from the main analysis. The variety of results suggests that further in-depth research on specific types of taxes could provide valuable insights into the impact of tax reforms on credit risk and other aspects of market functioning.

These findings provide important insight for the practical use of climate risk indicators. Firstly, despite the heterogeneity observed across countries, we have found a set that could be used for assessing asset classes that are the most exposed to climate risk. Secondly, presented correlations can impact the model estimation process regarding the initial selection of significant risk drivers. Therefore, it is important for risk managers to understand how these indicators are built and choose the most appropriate to their needs.

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Wpływ ryzyka klimatycznego na parametry ryzyka kredytowego Ocena na podstawie pięciu gospodarek UE

Streszczenie: Coraz częściej występujące ekstremalne zjawiska pogodowe, które stanowią element ryzyka klimatycznego, są jednym z kluczowych aspektów analizowanych obecnie przez instytucje finansowe. Niniejszy artykuł bada związek między wskaźnikami ryzyka klimatycznego a dwoma głównymi parametrami tradycyjnego procesu zarządzania ryzykiem: wskaźnikami niewypłacalności i wskaźnikami strat. Informacje te są cenne dla instytucji finansowych, umożliwiając im skuteczne zarządzanie ryzykiem związanym ze zmianami klimatu. Badanie wypełnia lukę naukową, wykorzystując nowe wskaźniki do analizy wpływu ryzyka klimatycznego na ryzyko kredytowe w największych gospodarkach UE. Autorzy przedstawiają wyniki dla pięciu największych gospodarek Unii Europejskiej (Niemiec, Hiszpanii, Włoch, Holandii, Francji) oraz wykazują silne, umiarkowane i słabe powiązania dla każdej pary czynników ryzyka klimatycznego i parametrów ryzyka kredytowego, wykorzystując trzy miary korelacji: Pearsona, Spearmana i Kendalla-Tau'a. Wyniki wskazują znaczące różnice między krajami, z największą liczbą skorelowanych zmiennych w Holandii. Wysoką korelację zaobserwowano również we Francji i Włoszech, podczas gdy w Hiszpanii i Niemczech korelacje były mniej wyraźne. Korelacje różnią się również w zależności od klasy aktywów, co podkreśla potrzebę indywidualnego podejścia do oceny ryzyka klimatycznego.

Słowa kluczowe: ryzyko kredytowe, zmiana klimatu, parametry ryzyka, testy warunków skrajnych, ryzyko klimatyczne

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