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TRABAJO FIN DE GRADO EN DOBLE GRADO INTERNACIONAL EN ADMINISTRACIÓN Y DIRECCIÓN DE EMPRESAS Y EN ECONOMÍA

CARBON EMISSIONS AND DEFAULT RISK

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Pamplona-Iruña 8 de septiembre de 2023

Módulo: Finanzas

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ABSTRACT

Given the growing importance of the climate risk at a global level, this work attempts to relate it to business and finance through the study of the effect of carbon emissions on the companies' probability of default risk. To this end, using panel regression models, the direct effects of carbon emissions on credit risk are analysed. We then study whether carbon footprint mitigation actions such as environmental expenditures, climate initiatives or executive compensation alter the effect of emissions on credit risk. As a result, we find that, on the one hand, the credit risk increases with a higher amount of carbon emissions, and, on the other hand, that such mitigation actions have the opposite effect, i.e. they reduce the effect of emissions on credit risk. To conclude, we highlight the need for companies to integrate climate risk management into their business strategies.

Key words: climate risk, default risk, carbon emissions, environmental expenses, climate initiatives.

RESUMEN

Dada la creciente importancia del riesgo climático a nivel global, este trabajo trata de relacionarlo con la actividad empresarial y las finanzas a través del estudio del efecto de las emisiones de carbono sobre el riesgo de impago de las empresas. Para ello, utilizando modelos de regresión de datos de panel, se analizan los efectos directos de las emisiones de carbono sobre el riesgo de crédito. A continuación, se estudia si las acciones de mitigación de la huella de carbono, como los gastos medioambientales, las iniciativas climáticas o la retribución de los ejecutivos, alteran el efecto de las emisiones sobre el riesgo de crédito. Como resultado, encontramos que, por un lado, la probabilidad de riesgo de crédito aumenta con una mayor cantidad de emisiones de carbono y, por otro, que dichas acciones de mitigación tienen el efecto contrario, es decir, que reducen el efecto de las emisiones sobre el riesgo de crédito. Para concluir, destacamos la necesidad de que las empresas integren la gestión del riesgo climático en sus estrategias empresariales.

Palabras clave: riesgo climático, riesgo de impago, emisiones de carbono, gastos medioambientales, iniciativas climáticas.

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1. INTRODUCTION

The involvement of business in the impacts of climate change is significant and is increasingly recognised as an important contributor to both negative impacts and solutions for mitigation and adaptation (Linnenluecke et al., 2013).

On the one hand, business activities play an important role in generating greenhouse gas emissions, which are mainly responsible for global warming. Businesses that rely on burning fossil fuels, such as energy, transport, and manufacturing companies, have contributed significantly to greenhouse gas emissions (Nasih et al. 2019). In addition, some corporate practices, such as deforestation for raw material extraction, have also contributed to the release of greenhouse gases and the loss of carbon sinks.

On the other hand, many companies are taking steps to reduce their carbon footprint and minimize their impact on climate change. More and more companies are adopting sustainable business practices and developing strategies to mitigate climate change (Surminski, 2013). These include adopting clean technologies, energy efficiency, reducing emissions, using renewable energy sources, and adopting circular approaches in their supply chains. Companies are developing climate risk management strategies and adapting their operations and business models to better withstand the impacts of climate change.

As the impacts of climate change intensify and become more evident, although many companies take actions with a wide range of initiatives, those that fail to act to address them, or do so in a poor manner, are expected to face increased financial risks, including the risk of default (Jung et al., 2018). Indeed, the increasingly stringent regulation and required technological change in the context of environmental demands by firms' stakeholders and civil society may compromise the viability of high carbon emitters.

Because the companies with larger carbon footprint are relatively more exposed to progressively stricter climate-related regulations, such as higher carbon taxes or more expensive carbon allowances in emissions trading schemes, their cash flows, for example, are expected to be affected to a larger extent than those of companies with a lower carbon intensity. Insufficient cash flow can lead a company to rely on additional credit or borrowing to cover its cash needs, which in turn can increase its debt burden and financing costs. If the company is unable to obtain the necessary financing or if its expenses exceed its cash generation capacity, it is more likely to experience financial difficulties and be at risk of default.

Studies investigating the impact of climate impacts on probability of default are limited (Bell and van Vuuren, 2022) because this is a novel field and emissions data are still relatively scarce. While the relationship between climate risks exposure and share prices is receiving growing attention by scholars and investors, the impact on default or credit appears relatively underexplored. In most cases, such as Löffler et al. (2021), default risk is used as a control variable and, therefore, the assessment of the default risk as a consequence of climate risk can be considered a field of study with potential for improvement.

This study contributes to this literature gap by investigating whether firm's exposure to climate risks by means of carbon emissions affects the corporates credit risk. Moreover, this study investigates if mitigation actions such as environmental expenses, climate actions or compensation to executives for reducing emissions, reduce the probability of default by decreasing its exposure to climate risk.

The study is structured in a first literature review in which the main articles related to this topic are reviewed, and the research gap is identified. Then, the database and the variables to be used during the study are defined, accompanied by an analysis of data availability. After that, a univariate and multivariate analysis is executed, where the descriptive statistics of the variables and the general and specific regression models are presented. Finally, the results of the global model are presented, followed by conclusions drawn from the impact of climate variables on the probability of default.

2. LITERATURE REVIEW AND HYPOTHESES

Existing literature is imputing climate risk into financial markets, via lower equity return or lower valuation for carbon-intensive firms, leaving corporate consequences aside. It mostly covers the analysis of the relationship between environmental issues and credit risk performance indicators, such as cost of equity (Sharfman and Fernando, 2008), loan contract conditions (Nandy and Lodh, 2012), cost of debt (Chava, 2014) and credit spreads (Oikonomou et al., 2014), showing in all cases that a better environmental performance is associated with better credit performance indicators.

Articles for financial markets are wide, Tan et al. (2022), for example, investigate whether bond markets reflect firms' exposure to air pollution through an increased cost of debt financing; and, if so, whether firms can mitigate this air pollution penalty via effective governance and active monitoring. They find a positive association between air pollution and the cost of debt financing, as well as that strengthened corporate governance, active board and external monitoring, and a stabilized economic environment further enhance the impact of air pollution on a firm's cost of debt.

Moreover, Andersson et al. (2016) propose a dynamic investment strategy in the decarbonized indexes that allows long-term passive equity investors to hedge climate risks without sacrificing financial returns. De Jong and Nguyen (2016) find similar hedging strategy for bond portfolio without sacrificing benchmark-tracking properties, but Boermans and Galema (2017) show that Dutch pension funds face intricate trade-offs when aiming to reduce portfolio carbon emissions.

As seen in these examples, most of the research on environmental risk and economics has been focused on financial markets, studying, among others, market indexes, and focusing a little on companies, bond and debt markets, and financial return. In any case, the interest between the negative effects of climate change and pollution and the consequences of these on business has not been nil.

Several studies point to the impact of climate risks on firm's competitiveness and financial performance. Bassi et al. (2009) examine the impacts of energy price changes resulting from different carbon-pricing policies on the competitiveness of selected US energy-intensive industries. The results show that climate policies that put a price on carbon could have substantial impacts on the competitiveness of energy-intensive manufacturing sectors over the next decades if no action is taken to invest in advanced low- and no-carbon technologies, explaining also that the extent of these impacts will vary across industries, depending on their energy intensities, the mix of energy sources they rely on and how energy is used in production activities.

However, specifically after the signing of the Paris Agreement in 2016, some of the interest in the credit risk field has shifted from the financial market discussion to the firm-level analysis, focusing on default risk. Rehman and Liu (2021), for instance, explore the impact of corporate default risk on environmental deterioration in the international context. They find that corporate bankruptcy is positively associated with CO2 emissions and its decomposed components.

Anyway, to relate environmental impact and credit risk, the existing literature uses several different methods, starting from different measures for calculating the environmental impact or the exposure to it, to the use of different measures for the valuation of a corporate's credit risk.

Nguyen and Huynh (2023), using a broad sample of U.S firms from 2002 to 2021, confirm the positive impacts of firm-level exposure to climate change risks on default risk, being the effect more pronounced for firms with greater financial constraints and leverage, as well as that carbon-intensive firms and sectors are affected more insensitively compared to carbon-non-intensive ones. To estimate the impacts, they use a model in which Distance to Default is the variable of interest. For that, the firm-level default risk is proxied by Distance to default, dependent on the climate change exposure of firm i in quarter t.

Kabir et al. (2021) measure how far a limited liability firm is from default depending on their carbon emissions. The study is based on total carbon emissions (TCE), direct carbon emissions (DCE), indirect carbon emissions (ICE), and Scope 3 carbon emissions for the analysis. On this study, using a panel dataset of 2785 unique firms over the period 2004–2018 from 42 economies, they document a significant and negative impact of emissions on firms' distance-to-default, as well as providing evidence that firms' environmental commitments and green initiatives mitigate the effect of emissions on default risk while environmental controversies exacerbate the effect.

From another point of view, being considered as a green firm helps build a corporate reputation in society, which is highly regarded by stakeholders, and, in turn, has a favourable effect on firms' revenue. On the contrary, firms engaging in carbon-emitting operations are likely to suffer from public outrage. Attig et al. (2013) argue that the dangers of behaving socially irresponsible are realised through a decrease in firms' intangible assets, including reputation and relationships, which might further translate into income and market share loss. The reduced market share due to the loss of competitiveness might increase future cash-flow uncertainty, which could significantly increase firms' risk of default.

As we have seen, to calculate the variables of interest, several methods are used in the articles found, using climate risk exposure or carbon emissions to analyse the environmental impact, and using an overview of credit risk or the "Distance to Default" approach, and the effect on corporate image to assess a company's probability of default.

Furthermore, it is worth noting that all these studies focus on data obtained from US or Asian companies, while studies on European countries are more difficult to find, therefore, it can be said that the effects that can be found in a European environment have been only vaguely analysed.

This paper, by studying Carbon Emissions and the probability of default, differs from prior studies in that it includes a geographical framework of companies not previously studied, as well as including in the same model variables that increase climate impact and others that aim to mitigate it.

To this end, the first hypothesis to be studied is:

H1: The higher the carbon emissions, the higher the probability of default.

On the other hand, Gutiérrez-López et al. (2022) analyse the impact of environmental performance on default risk as firms advance to low-carbon production, via environmentally related investments. The results indicate a greater distance to default for better carbon performers that are more advanced in their transition to lower-carbon production.

In this sense, our next hypotheses focus on the use of environmental related expenses that aim to either directly reduce carbon emissions, or for proactive environmental investments to promote energy transition so as to reduce future risks or increase future opportunities. Our second and third hypotheses state that:

H2: Environmental expenses by companies reduce their probability of default.

H3: Climate risk mitigation actions reduce the company's probability of default.

Lastly, the relationship between CEO offsets to reduce their company's carbon emissions and credit risk can be complex and influenced by a number of factors. If CEO rewards are linked to the achievement of carbon reduction targets, this may incentivise greater attention and commitment to sustainability in the company. Emissions reductions can result in long-term benefits, such as improved operational efficiency, regulatory risk mitigation and reputational enhancement, which could reduce credit risk.

In addition, proactive management of carbon emissions can help the company avoid future regulatory costs, fines and risks associated with climate change. This could reduce exposure to unanticipated financial risks and improve creditworthiness.

We therefore put forward a fourth hypothesis:

H4: Incentives offered to executives to reduce carbon emission decrease its company's probability of default.

Large companies tend to have a larger carbon footprint due to their size and scope (Nasih et al., 2019), but they also have the capacity and resources to implement meaningful measures to reduce these emissions. Smaller companies, on the other hand, may have more modest carbon footprints, but their environmental impact depends largely on their industry, sustainability practices and commitment to emissions reduction. Therefore, we put forward a fifth and final hypothesis:

H5: The effect of carbon emissions on credit risk is higher for larger companies.

3. DATABASE AND METHODOLOGY

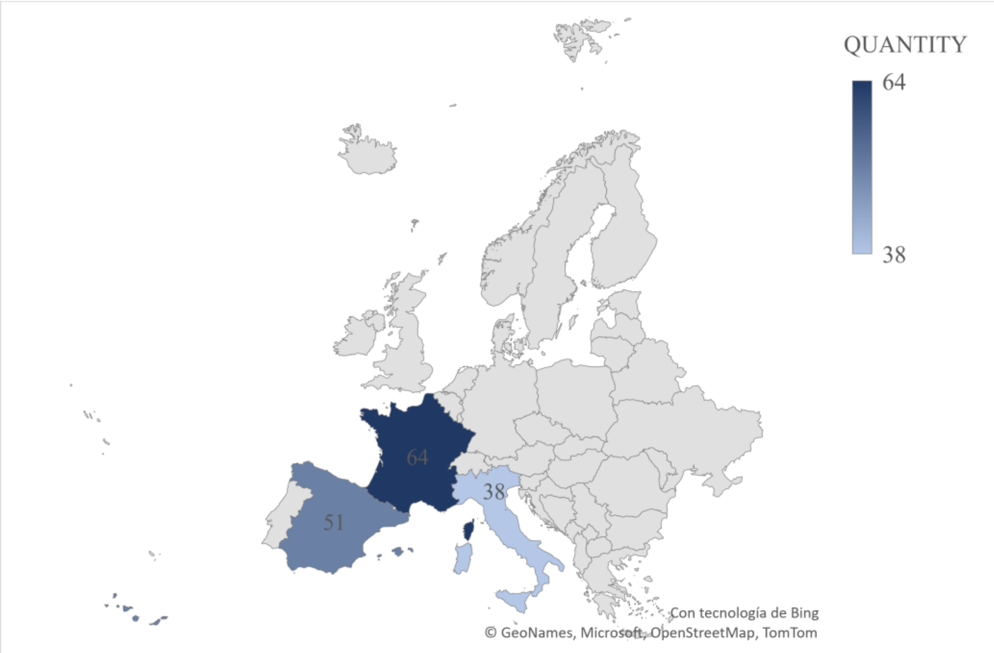
Once the most relevant literature has been reviewed and we have clarified some concepts, we can move on to perform our own empirical analysis with the objective of testing the stated hypothesis. But before presenting our results, it seems pertinent to describe our database and present the key variables for the study.

3.1 Database

Data are obtained from Eikon Refinitiv database. We consider data from Spain, France and Italy, and we filter for the companies with information available about carbon emissions and with data for obtaining the measure of default risk, which we explain later. We exclude companies from the financial sector due to their particular capital structure. Starting with an initial sample of 8,203 companies, after filtering, we obtained data of 153 Spanish, French and Italian firms from 2000 until 2022. The information obtained includes environmental related and market data. Specifically, we select the following data for the calculation of the credit risk variable, which are the ones included in the most commonly used measures of default risk, such as the Black-Scholes-Merton measure of distance to default, short-term liabilities, long-term liabilities, EBIT, total assets, total debt, and market to book value ratio. The variables to be used in the model include carbon emissions, environmental expenses, environmental initiative, sustainability compensation, market value, book-to-market, leverage and ROA.

Figure 1 illustrates the distribution of companies by country, by adding the number of companies found in each of the countries studied.

Figure 1. Map of distribution of companies by country



As can be seen in the graph, the majority of companies in the sample come from France, with a total of 64 companies, followed by Spain (54), and then Italy (38).

The reason for choosing these three countries for the study is that, in addition to the few studies in this area conducted in Europe, companies located in Spain, Italy and France face several common credit risk factors due to their proximity, the nature of their economies and the business conditions in the European region. Indeed, Italy, France and Spain share markets due to a combination of their geographic proximity, their membership in the European Union, their shared history and the complementarity of their economies. As a result, these factors have driven a continuous economic interaction between the countries over time, which can lead to the creation of trade agreements between them, or even the same negative impact on markets in which they are competitors.

Companies in these nations often have close business relationships with each other. Financial difficulties in one country can have a ripple effect on supply chains and business transactions in the other two nations. This condition is also compounded by the fact that economic conditions in these countries may be similar, meaning that all of these companies will be influenced by the same economic trends, such as economic recessions or expansions.

On the other hand, companies in Spain, France and Italy may face similar competition in the European market, which could lead to pressures on profit margins and the ability to meet debt obligations. Given that Spain, France and Italy are popular tourist destinations, for example, companies in tourism-related sectors may be affected by variability in tourist inflows, which could impact their cash flows.

3.2 Key Variables

As it has been previously mentioned, the principal objective of this paper is to examine the relationship between carbon emissions and credit risk, assessing also if environmental initiatives or sustainability compensations to managers affect a company's distance to default. For this, it is appropriate to present the key variables for the study and explain how we will measure them.

3.2.1 Measure of Default Risk

In order to measure default risk, we use the model proposed by Bharath and Shumway (2008), which is a naïve version of the structural model known as Black-Scholes-Merton (BSM) measure to avoid the iterative process needed to implement the BSM measure.

The BSM measures is based on the framework of Merton (1974), in which the equity of the firm can be seen as a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt. The model recognizes that neither the underlying value of the firm nor its volatility are directly observable. Under the model's assumptions both can be inferred from the value of equity, the volatility of equity, and several other observable variables by using an iterative procedure to solve a system of nonlinear equations, and starting from the Black-Scholes (1973) option-pricing model. After inferring these values, the model specifies that the probability of default is the normal cumulative density function of a z-score depending on the firm's underlying value, the firm's volatility, and the face value of the firm's debt.

Bharath and Shumway (2008), instead of using this iterative procedure, propose a fixed relationship between the volatility of equity and the assets volatility, which avoids the iterative procedure. The expression of the probability of default under their model is given by the following expressions:

$$P_{i,t}^{def} = N\left(-\frac{ln\frac{E_{i,t}+D_{i,t}}{D_{i,t}}+\left(r_{i,t}-\frac{\sigma_{A_{i,t}}^2}{2}\right)(T-t)}{\sigma_{A_{i,t}}\sqrt{T-t}}\right) \tag{1}$$

with:

$$\sigma_{A_{i,t}} = \frac{E_{i,t}}{E_{i,t}+D_{i,t}}\sigma_{E_{i,t}} + \frac{D_{i,t}}{E_{i,t}+D_{i,t}}(0{,}05 + 0{,}25\sigma_{E_{i,t}}) \tag{2}$$

and where $E_{i,t}$ is the market capitalization of the firm i at t; $D_{i,t}$ is the face value of the debt; $r_{i,t}$ is the past annual return of the firm; $\sigma_{Ei,t}$ is the annual volatility of the stock value; $\sigma_{Ai,t}$ is a proxy for the volatility of the market value of the firm's total assets; T-t is the time to maturity; and N(·) is the cumulative probability of the Normal distribution (0,1). We take T-t = 1 year as in other works (Vassalou and Xing, 2004; Gharghori et al., 2006) and the face value of debt as the sum of short-term debt plus half of long-term debt.

The resulting value will equate the probability of a company's default risk, thus, taking a value between 0 and 1, being 1 a 100% probability of default. Consequently, the dependent variable to be analysed in the study will be the probability of default (RC).

3.2.2 Explanatory Variables

3.2.2.1 CO2 Emissions

The variable of interest of this study accounts for Total Carbon dioxide and CO2 equivalents emission in tonnes (CO2.EMIS). Indeed, it reflects the direct emissions from sources that are owned or controlled by the company (scope 1 emissions), as well as indirect emissions (scope 2), which include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCS), perfluorinated compound (PFCS), sulfur hexafluoride (SF_6), and nitrogen trifluoride (NF_3). The database follows greenhouse gas (GHG) protocol for all their emission classifications by type.

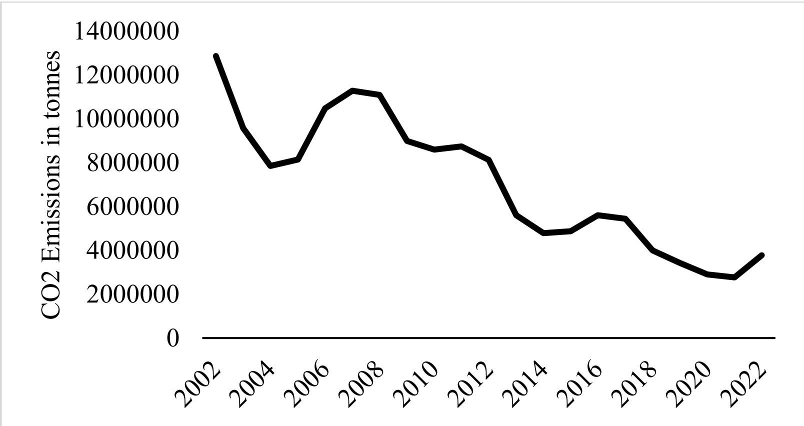
The variable to be included in the regression model of the study will be the logarithm of this value of CO2 emissions and equivalents (l_CO2EMIS), in order to provide stability in the regressors, reduce outliers and establish different views of the estimation.

Carbon emissions can affect a company's credit risk in a number of ways. Thus, governments and international organisations, for example, are implementing stricter regulations to reduce carbon emissions and mitigate climate change. Companies that emit large amounts of carbon could face significant costs due to fines, carbon taxes or other regulatory measures. These additional costs can affect the profitability and debt repayment capacity of the company, increasing its credit risk.

Therefore, we expect the relationship between credit risk and CO2 emissions in our model to be negative, i.e. a reduction in CO2 equivalent emissions increases a firm's distance to default.

Figure 2 shows the average CO2 emissions per year of the companies included in the data sample.

Figure 2. Average Carbon Emissions between 2002 and 2022



It is clear that emission levels are drastically reduced during the period under study, even if the trend is still downwards, an irrefutable proof of the energy transition that has been so much discussed during the last years.

For the purpose of this study, these results lead us to assume that the probability of default also decreases as emissions fall, however, this may not be reflected given the other factors that directly affect credit risk, such as Market Value, Book-to-Market, or financial leverage and ROA.

3.2.2.2 Environmental Expenses

Another variable of interest presented in this model is the total amount of environmental expenditures made by each company (ENVEXP). What this shows us is all environmental investment and expenditure for the protection of the environment or to prevent, reduce, control environmental aspects, impacts and hazards. It also includes the costs of disposal, treatment and clean-up. For this case we will also use the logarithm of the values obtained from the database (l_ENVEXP).

Investments in more energy-efficient technologies and natural resource management not only reduce environmental impacts but can also generate significant savings in long-term operating costs. This improves the company's profitability and its ability to meet its debt obligations.

This is why we expect a positive relationship between this variable and the company's default risk, since the more the company invests in sustainability, the lower the climate risk, and therefore the greater the distance to default (the lower the probability of default).

3.2.2.3 Climate Investment Initiatives

This variable reflects if the company reports on making proactive environmental investments or expenditures to reduce future risks or increase future opportunities (CLIMATEACT). These investments or expenditures involve investment made in the current fiscal year so as to reduce future risks and increase future opportunities related to the environment, investments made in new technologies to increase future opportunities, or expenditures for treatment of emissions (e.g., expenditures for filters, agents) or installation of cleaner technologies.

For this case we will use a dummy variable, which will have a value equal to 1 if the company reports in that year that they have made investments to improve the sustainability of the company, and 0 if the opposite is the case. We expect to find a positive relationship, that the distance to default increases when the company reports environmental initiatives.

It is of great interest to study this variable because companies that adopt responsible environmental practices may be better prepared to deal with risks related to extreme events, such as natural disasters and climate change. Planning and investment in resilient infrastructure and disaster preparedness can reduce losses and impact on operations, which in turn preserves financial stability.

3.2.2.4 Executives' Compensation

The last explanatory variable of the model shows whether the senior executive's compensation is linked to CSR/H&S/Sustainability targets (COMPEXEC). For this case we will analyse if the incentives offered to the manager to reduce the company's climate impact will indeed have an effect on the company's emissions, and thus on the credit risk.

Linking senior management pay to CSR/SG/Sustainability objectives ensures that company leaders have a vested interest in achieving sustainable goals. This could result in decisions and actions that are more aligned with the long-term interests of the company, reducing the likelihood of excessive risk-taking that could increase credit risk. Indeed, if senior management is incentivised to address these risks proactively, the company may be better prepared to avoid adverse events that could affect its financial position and thus its credit risk.

For this case we will also use a dummy variable, which will take the value of 1 if in that company and year the CEO has incentives to reduce climate impact, and 0 otherwise. We expect the relationship between this variable and the distance to default to be positive, with the distance to default increasing if these incentives reduce emissions, and hence credit risk.

3.2.3 Control Variables

In the model we will use to analyse the relationship between credit risk and companies' carbon emissions, we will also include some control variables that will help us to control or adjust the effect of other independent variables that may affect credit risk.

These variables are market data and the financial situation of the companies, which are closely related to the default risk of the companies. These variables are: Market Value (MV), measured as market capitalization, Book-To-Market (BTM), Return on Assets (ROA) and Leverage (LEVERAGE), expressed in thousands of euros. A logarithm will be also used to include MV in the regression model (l_MV).

These market data enrich the models by providing additional information about the company and its economic environment. This can help to model more accurately how carbon emissions affect credit risk, as they can anticipate or signal future trends in credit risk. If carbon emissions are correlated with changes in stock prices or credit ratings, this could indicate a possible increase or decrease in credit risk in the future.

3.2.4 Data availability

To demonstrate the reliability of this study, we present the data availability of the database selected. With the aim of measuring data availability, we have counted the number of variables available for each firm for each year, considering the aforementioned eight variables. Since we require at least information for Emissions and Market Value variable, the number of variables available ranks from 2 to 8. In case a company doesn´t have information on Emissions or Market Value, the variable of data availability is an empty data. In Table 1 we can see this information both, by company and by year.

Table 1. Number of variables by firm-year

By Company and Year		
Maximum	Minimum	Mean
8	2	7,00828

Furthermore, in Table 2 we show similar information but by variable, indeed, it is illustrated the number of variables each company presents in a 23-year time range. We can notice that the least available variable is Environmental Expenses, while the most available variable after market value is Leverage.

Table 2. Availability of data by variable by company-year

	By Company and Year		
	Maximum	Minimum	Mean
Carbon Emissions	21	1	10,69211
Environmental Initiative	21	1	13,00622
Environmental Expenses	20	1	7,94497
Sustainability Incentive	21	0	13,05142
Market Value	23	6	19,55988
Book-To-Market	23	1	19,22120
ROA	23	4	20,04614
Leverage	23	7	20,35733

For instance, regarding 'Carbon Emissions', the minimum amount of data available is one. This means that there are companies that only have data available regarding their amount of carbon gasses emitted in one year among all the range selected.

If we look at the "Mean" column, we observe that there are noticeable differences between variables. As an illustration, we observe that 'Carbon Emissions' and 'Environmental Expenses, are the variables for which the least amount of data is available by company throughout the years, with an average of 10,7 and 7,94 respectively. On the other hand, 'Leverage' is the variable with the highest amount of data available throughout the years, with an average of "20.35".

4. UNIVARIATE ANALYSIS

The aim of this section is gaining some first insights about the panel created, the companies' sample, and their respective variables. This is done considering the final purpose of the study, which is measuring the effect of CO2 emissions on the selected companies' probability of default.

Firstly, the main descriptive statistics are computed for the whole sample. The next Table 4 presents the descriptive for the different model variables.

Table 3. Main descriptive statistics

	RC	C02.EMIS	CLIMATEACT	ENVEXP	COMP.EXEC	MV	BTM	LEVERAGE	ROA
MEAN	0,03066	12,84356	0,44231	16,48143	0,31104	21,98008	2,48862	0,31010	0,05918
SD	0,11166	2,67465	0,49678	2,44334	0,46303	1,60500	12,47982	0,17291	0,06606
MIN	0	3,66356	0	6,47235	0	16,90063	-66,74000	0	-0,35755
MEDIAN	0,00000000482	12,91047	0	16,63810	0	22,02170	1,59500	0,30427	0,05748
MAX	0,99195	18,89229	1	22,49400	1	26,62851	646,71000	1,83226	0,98847

As it is obvious, we find very disparate averages between all the variables, since some such as RC, CLIMATEACT, COMP.EXEC or ROA only take values between 0 and 1, or LEVERAGE which is a ratio, while the values of the logarithms of CO2.EMIS, ENVEXP or MV can adopt significantly higher values.

Among them, the credit risk variable is worth highlighting, as it shows us how we find companies that are in totally opposite situations in terms of their probability of default, as it shows a minimum probability of 0 and a maximum of 0.99195. However, through the median we identify that most of the companies have a probability closer to 0. Furthermore, we find that the distribution of credit risk is skewed to the left.

On the other hand, if we look at the CO2.EMIS logarithm data, we can see that the mean and median have an almost identical value, and this, together with the high value of the standard deviation, is an indicator that the values of CO2 emissions among the companies are very dispersed. These findings are significant given the large difference between the maximum and minimum value they adopt, so we also expect significant differences in credit risk.

The case for environmental expenses is very similar. We find a significant difference between the minimum and the maximum, as well as a high level of standard deviation, so for this case we also assume that the values are very dispersed. Furthermore, we see that the median is very high, which shows that most of the companies take large measures regarding their environmental impact, which should reduce the credit risk.

To conclude with the descriptives, the results show that for the two dummy variables e CLIMATEACT and COMPEXEC, the median is equal to 0 and the mean is less than 0.5, meaning that we find more companies that do not take environmental initiatives or do not compensate their executives for reducing climate impact than those that do.

Then, Table 4 presents the correlation matrix, showing the coefficients for all variables included in the study.

Table 4. Correlation matrix

	RC	C02.EMIS	CLIMATEACT	ENVEXP	COMP.EXEC	MV	BTM	LEVERAGE
C02.EMIS	-0.0612**							
CLIMATEACT	0.0255	0.2244***						
ENVEXP	-0.0181	0.7068***	0.2421***					
COMP.EXEC	0.0064	0.121***	0.1774***	0.1764***				
MV	-0.158***	0.2709***	0.0565***	0.4395***	0.1592***			
BTM	-0.0158	0.0108	-0.0489**	-0.0179	-0.0382*	0.0051		
LEVERAGE	0.18***	0.1053***	0.0644***	0.1386***	0.0701***	0.0001	0.0251	
ROA	-0.2257***	-0.0332	-0.0266	-0.0857***	-0.0854***	0.0791***	0.0078	-0.1672***

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.

The first value shown in the table, which shows the correlation between the credit risk and CO2 emissions, contradicts, in principle, our hypothesis number 1. In it, we hypothesised that credit risk would increase with the increase in emissions. On the contrary, this negative correlation implies that as a company's emissions increase, its credit risk should decrease. However, we must consider that in the correlation matrix we only show the relationship tow-by-two variables, without taking into account the rest of the variables considered in the study. These impacts of the descriptive variables on the dependent variable will be studied in more depth in the next section.

Regarding the other three explanatory variables, we observe that the correlation coefficients between them and the default risk are not significant. In the case of the control variables, we find a positive and significant relationship between default risk and leverage, while a negative one between market value and ROA with default risk, respectively.

In this correlation matrix it is also interesting to study the relationships between the explanatory variables, since we include the explanatory variable of interest, which is CO2 emissions, and other descriptive variables that are related to it. Thus, we have the ENVEXP variable, which explains the amount in euros that have been invested to reduce the environmental impact, in other words, to reduce emissions. We can see that companies with more CO2 emissions have more environmental expenses. Similarly, we see how the

CLIMATEACT variables, indicating whether or not measures are being taken to reduce environmental impact, and COMPEXEC, indicating whether executives receive compensation for reducing emissions, also have a positive relationship in terms of CO2 emissions. To check the reliability of these descriptive variables that are related to each other, we see that the correlation between the variables describing environmental expenditures and whether initiatives are taken to reduce environmental impact is positive. Thus, it is shown that when companies take environmental actions, the expenses incurred for it also increase.

Finally, to conclude the preliminary analysis, a test of mean differences for credit risk attending to different variables is presented, in which the null and alternative hypotheses tested are, respectively: (H_0) difference of means equals 0, or (H_1) exists difference of means. However, before the means test, a contrast analysis of variances has been carried out by using the test statistic calculator of Gretl, which is needed for the mean differences test. Indeed, if in the contrasts of variance, we reject the null hypothesis because the p-value is lower than the significance level, we assume the population variances are different during the means test.

This study of the difference of means will be useful for this study, as it shows how the mean of credit risk changes depending on whether the variable studied is higher or lower than its mean. To do so, a dummy was calculated for each variable, by year and company. These variable dummies are equal to 1 if the value of that year and company is greater than the median of that variable, and 0 if the value is less than the median. Table 5 presents the results.

Table 5. Difference of means with respect to the dependent variable RC

	RC(dummy=1)	RC(dummy=0)	Difference
CO2.EMIS	0,03329	0,03638	-0,00309
CLIMATEACT	0,03705	0,03087	0,00618
ENVEXP	0,01540	0,02928	0,01388**
COMP.EXEC	0,03467	0,03300	0,00167
	RC(dummy=1)	RC(dummy=0)	Difference
MV	0,01910	0,03450	−0,01540***
BTM	0,00772	0,03899	−0,03126***
ROA	0,00459	0,05470	−0,05011***
LEVERAGE	0,04817	0,01447	0,03370***

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.

As with the correlation table, the results of the table are quite interesting, as they somewhat contradict our hypotheses. Regarding the explanatory variables, we only find differences when we attend to the ENVEXP classification. Thus, we observe that companies with higher environmental expenses present a higher default risk.

The results for the control variables are significant at 1%, and indicate that credit risk is lower when the values of market value, book-to-market and return on assets are high, while credit risk is higher when leverage is higher.

5. MULTIVARIATE ANALYSIS

The purpose of this section is presenting and explaining the different models' estimations. For all models the dependent variable is the probability of default (RC) measured under the Bharath and Shumway (2008) model. Firstly, three general models are presented (see Table 6) in which only the effect of the control variables are included, moving from a basic one which incorporates one constant and two control variables, to more complex ones including all the control variables.

Table 6. General models for control variables

CONTROL MODELS	
1	$RC_{i,t} = \beta0 + \beta1RC\_1_{i,t-1} + \beta21\_MV_{i,t} + \beta3BTM_{i,t}$
2	$RC_{i,t} = \beta0 + \beta1RC\_1_{i,t-1} + \beta21\_MV_{i,t} + \beta3BTM_{i,t} + \beta4LEVERAGE_{i,t}$
3	$RC_{i,t} = \beta0 + \beta1RC\_1_{i,t-1} + \beta21\_MV_{i,t} + \beta3BTM_{i,t} + \beta4LEVERAGE_{i,t} + \beta5ROA_{i,t}$

$RC_{i,t}$ is the credit-risk measure for company i in the period t between 2000-2022, $RC_{i,t-1}$ is the lagged credit-risk measure for company i. $l\_MV_{i,t}$ determines the market value of company i, measured by the logarithm of its value. $BTM_{i,t}$, determines the market value of a company relative to its actual worth, in a given period of time, t. Besides, $ROA_{i,t}$, determines company i's profitability.

Since the credit risk (RC) variable is persistent, the effects of the variable may not manifest themselves immediately, but may take time to take effect. Therefore, we include the lag $RC_{i,t-1}$ in the model, as including lags of the dependent variable allows these lagged effects to be reflected in the model.

The regression models presented in this paper are estimated using panel data models with fixed effects.

Furthermore, after having presented the general models for the control variables, extra components of the explanatory variables are incorporated to examine whether the relationship between the dependent variable these descriptive and/or control variables is more or less significant. For this reason, in the following specific models shown in Table x, each of the descriptive variables are studied one by one, considering the basic structure of models 1 to 3 (see Table 7). The study of each descriptive variable is cascaded by adding one more control variable at each step, to see the specific impact of the inclusion of each component.

Table 7. Specific models

SPECIFIC MODELS	
CO2.EMIS	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 21\_CO2.EMIS_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t}$
	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 21\_CO2.EMIS_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t} + \beta 5LEVERAGE_{i,t}$
	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 21\_CO2.EMIS_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t} + \beta 5LEVERAGE_{i,t} + \beta 6ROA_{i,t}$
ENV EXP	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 21\_ENVEXP_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t}$
	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 21\_ENVEXP_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t} + \beta 5LEVERAGE_{i,t}$
	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 21\_ENVEXP_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t} + \beta 5LEVERAGE_{i,t} + \beta 6ROA_{i,t}$
CLIMATEACT	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2CLIMATEACT_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t}$
	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2CLIMATEACT_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t} + \beta 5LEVERAGE_{i,t}$
	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2CLIMATEACT_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t} + \beta 5LEVERAGE_{i,t} + \beta 6ROA_{i,t}$
COMPEXEC	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2COMPEXEC_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t}$
	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2COMPEXEC_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t} + \beta 5LEVERAGE_{i,t}$
	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2COMPEXEC_{i,t} + \beta 31\_MV_{i,t} + \beta 4BTM_{i,t} + \beta 5LEVERAGE_{i,t} + \beta 6ROA_{i,t}$

5.1 Control Models

This section presents all the models including the only MV, BTM, LEVERAGE and ROA control variables, as well as the 1 year lagged credit-risk measure. The results can be seen in the table 8.

The results, which are significant for all the variables in each model, show how the credit risk of the previous year positively affects the credit risk of the year studied to a large extent. Even so, its effect decreases when other control variables are included.

Table 8. Results of general models

	Model 1	Model 2	Model 3
Constant	0.662082***	0.620676***	0.599948***
RC_1	0.258813***	0.244505***	0.246853***
l_MV	−0.0290073***	−0.0284569***	−0.0272011***
BTM	−0.000237245*	−0.000258745*	−0.000262575*
LEVERAGE		0.0974417***	0.0888449***
ROA			−0.0777790**
R^2	0.449027	0.454253	0.409595

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.
Year and country fixed effects

The results, which are significant for all the variables in each model, show how the credit risk of the previous year positively affects the credit risk of the year studied to a large extent. Even so, its effect decreases when other control variables are included.

The market variables l_MV and BTM, on the other hand, have a negative relationship. These results are logical, as a higher value of these variables indicates a higher stability of the firm, which reduces credit risk. The impact of these variables is offset as the LEVERAGE and ROA variables are included, so that, as with the value of the constant, their impact is reduced when all variables are included. In any case, we see that the one with the least impact is BTM, followed by l_MV.

The market variables that have the greatest effect, after the lagged credit risk, are those included in models 2 and 3, i.e. LEVERAGE and ROA. While LEVERAGE, showing the level of debt of a firm, has a positive effect on credit risk, ROA, indicating the profitability of a firm, has a negative effect.

The R^2 value added at the end of the table indicates the proportional amount of variation in the dependent variable RC, explained by the independent variables included in the linear regression model. The higher the R-squared, the greater the variability explained by the model. In this case, we see how the R^2 value becomes smaller as more variables are included, which makes the model less explanatory.

5.2 Carbon Emissions

In this section, we analyse the impact of the carbon emissions on the probability of default.

As we assumed in hypothesis 1 (H1: The higher the Carbon Emissions, the higher the probability of default), we observe in Table 9 that the CO2.EMIS emissions variable has a positive effect with respect to RC, showing how an increase in the level of emissions increases the probability of default of firms.

Table 9. Results for specific models for CO2 emissions

	Model 4	Model 5	Model 6
Constant	1.05709***	0.968081***	0.962728***
RC_1	0.188110***	0.174399***	0.180637***
l_CO2EMIS	0.00896615**	0.00910862**	0.00902900**
l_MV	−0.0506509 ***	−0.0482448***	−0.0476829***
BTM	−0.000125527	−0.000133084	−0.000139865
LEVERAGE		0.106737***	0.0936102***
ROA			−0.0510151
R^2	0.531582	0.535354	0.539097

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.
Year and country fixed effects

As for the effect of the control variables, we observe that the signs are maintained with respect to Table 8, but the coefficients for BTM and ROA are no longer significant.

5.3 Environmental Expenses

Table 10 shows the results obtained by including the logarithm of the ENVEXP variable in the general models. The results follow the same pattern as previously studied, the constant with a significantly high coefficient and the lag of the dependent variable with a positive value.

Table 10. Results for specific models for Environmental expenses

	Model 7	Model 8	Model 9
Constant	0.914608***	0.837698***	0.816447***
RC_1	0.0600895*	0.0498566	0.0513430
l_ENVEXP	0.00324799***	0.00338433***	0.00357481***
l_MV	−0.0419393	−0.0399002	−0.0386497
BTM	−4.95239e-05	−5.61721e-05	−6.21949e-05
LEVERAGE		0.0908444**	0.0744562*
ROA			−0.0764796
R^2	0.537145	0.539631	0.540498

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.
Year and country fixed effects

It is worth highlighting the impact of the explanatory variable, since, despite expecting a negative effect on the probability of default, i.e. that the probability decreases as more money is invested in dealing with the environmental impact, the impact is positive, indicating exactly that by increasing the value of the logarithm of ENVEXP by 1, the probability of default increases by 3.57%.

Although we see that the credit risk increases with higher environmental expenditures, this may be due to the high correlation between carbon emissions and environmental expenditures. Thus, larger firms, those with higher carbon emissions and at the same time a higher probability of default, are the ones that compensate more through these expenditures, thus demonstrating a relationship between credit risk and expenditures.

5.4 Climate Initiatives

This section illustrates the effect of whether firms take climate impact initiatives in relation to credit risk. Table 11 shows the coefficients of the variables in the general models, and including in these specific models the dummy variable CLIMATEACT, which will only take values of 1 if initiatives are taken, and 0 otherwise.

As for the descriptive variable CLIMATEACT, the results indicate that if firms take climate initiatives, default risk increases by 1.8%, which is the complete opposite of what was hypothesised in the previous hypotheses. However, these results go hand in hand with those obtained in the mean difference, as a higher credit risk was found when environmental initiatives were taken. Again, we can see a relationship between large companies and emissions, as those companies that emit the most are at the same time the ones that take the most action to remedy it.

Table 11. Results for specific models for Climate Initiative

	Model 10	Model 11	Model 12
Constant	1.02081***	0.953660***	0.948103***
RC_1	0.230154***	0.218599***	0.222797***
CLIMATEACT	0.0188623***	0.0185563***	0.0181599***
l_MV	−0.0446280***	−0.0428539***	−0.0422883***
BTM	−0.000158259	−0.000178261	−0.000181779
LEVERAGE		0.0908379***	0.0795354***
ROA			−0.0646665***
R^2	0.487454	0.490926	0.495839

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.
Year and country fixed effects

The results are significant, but with a low R2 value. The model becomes more explanatory with the inclusion of the control variables, although still very little variability of the dependent variable is explained if only these descriptive and control variables are added.

5.5 Compensations for Executives

Finally, we show the multivariate analysis combining the control variables and the descriptive variable COMPEXEC. Table 12 shows the values of the coefficients of these variables.

Table 12. Results for specific models for Compensation for Executives

	Model 13	Model 14	Model 15
Constant	1.04584***	0.982292***	0.975570***
RC_1	0.231373***	0.221441***	0.225940***
COMPEXEC	0.0165068***	0.0143400***	0.0134000***
l_MV	−0.0456018***	−0.0438393***	−0.0431915***
BTM	−0.000160876	−0.000180084	−0.000184238
LEVERAGE		0.0816033***	0.0691070**
ROA			−0.0665082*
R^2	0.487297	0.490046	0.494785
*** , ** and * denote significance at the 1%, 5% and 10%, respectively.			
Year and country fixed effects			

The results, which are significant and become more explanatory of the dependent variable by including all the control variables, show that if firms offer rewards to managers for reducing climate impact, without changing the other variables, credit risk increases by 1.3%.

The results for this descriptive variable also go against the assumptions made in the hypotheses described in section 2. However, these results go hand in hand, again, with those obtained for the correlation coefficients, since those companies that emit the most are also those that compensate the most, thus linking compensation and credit risk.

It should be remembered that these models are specific to each descriptive variable, to observe trends and patterns. In the following sections, by building the overall model including each and every descriptive and control variable, we will be able to observe the true impact of each one on the credit risk.

6. MODERATING EFFECTS

After performing the multivariate analysis, we can see that several results obtained contradict the hypotheses presented in section 2, as well as hypotheses 2, 3 and 4, which assume that credit risk decreases as the emissions, initiatives or offsets variables take higher values. On the other hand, we see that the first hypothesis 1 is fulfilled, since the probability of default increases as carbon emissions increase.

Looking at the correlation matrix, which indicates a positive relationship between the carbon emissions variable (l_CO2. EMIS) and the other descriptive variables (l_ENVEXP, CLIMATEACT and COMPEXEC), and, at the same time, to the Nasih et al. (2019) study, which shows that large firms are the ones that emit and offset the most, we assume that these contradictory results are linked to these effects, i.e. that large environmental expenditures, initiatives or executive compensation do not offset the significant effect of emissions on default risk, and therefore, that climate mitigation activities and credit risk are positively related.

As a result, in this section we repeat the models presented above, but including one more variable, which will be an interaction variable between emissions and the other descriptive variables, which will serve to control for the actual effects of the descriptive variables.

In addition, for these cases inwhich we include the interaction variables in the models, we will perform a Wald test to check their significance level. The aim of this test is to find out whether the interactions included in the models are significant for the results. To do this, we will test whether the sum between the coefficient of the carbon emissions variable (l_CO2.EMIS) and the coefficient of the interaction (effect of emissions on credit risk when the selected dummy is equal to 1) is different from 0.

In this way, looking at the p-value, if it is less than 0.1, the test will indicate that the sum of these coefficients is different from 0, so we can conclude that the effect of emissions when the value of the controlled variable is high, is significant.

6.1 Controlling for emissions and company size

The first of the effects we will control for will be firm size, as larger firms emit more. Thus, the variable to include will be the interaction between carbon emissions (l_CO2EMIS) and the market value dummy (dummyMV). The result is l_CO2EMIS*dummyMV.

By including this interaction, we will have, on the one hand, the effect of emissions for small firms, only the coefficient of l_CO2EMIS (since if the firm is small the market value dummy is equal to 0 and the interaction has no effect); and on the other hand, the effect for firms, which will be the sum of the coefficient of variable l_CO2EMIS and the interaction l_CO2EMIS*dummyMV.

Recall that the model for this assumption is different, as it includes additional variables to identify the effect of emissions depending on whether it is a large or small firm. Therefore, the model will be as follows:

Table 13. Specific models for firm size control

MODELS CONTROLLING FOR EMISSIONS AND COMPANY SIZE	
16	$RC_{i,t} = \beta0 + \beta1RC\_1_{i,t-1} + \beta21\_CO2EMIS_{i,t} + \beta31\_CO2EMIS_{i,t}*dummyMV_{i,t} + \beta4dummyMV_{i,t} + \beta5BTM_{i,t}$
17	$RC_{i,t} = \beta0 + \beta1RC\_1_{i,t-1} + \beta21\_CO2EMIS_{i,t} + \beta31\_CO2EMIS_{i,t}*dummyMV_{i,t} + \beta4dummyMV_{i,t} + \beta5BTM_{i,t} + \beta6LEVERAGE_{i,t}$
18	$RC_{i,t} = \beta0 + \beta1RC\_1_{i,t-1} + \beta21\_CO2EMIS_{i,t} + \beta31\_CO2EMIS_{i,t}*dummyMV_{i,t} + \beta4dummyMV_{i,t} + \beta5BTM_{i,t} + \beta6LEVERAGE_{i,t} + \beta7ROA_{i,t}$

Table 14 below shows the results for these specific models in which we included the control for the size of the firms.

Table 14. Results for specific models for controlling for company size

	Model 16	Model 17	Model 18
Constant	−0.0185572	−0.0722759	−0.0577306
RC_1	0.229060***	0.206604***	0.212965***
l_CO2EMIS	0.00449512*	0.00508431	0.00512382
l_CO2EMIS*dummyMV	0.00270568**	0.00253343**	0.00296761**
dummyMV	−0.0685328	−0.0662072	−0.0697130
BTM	−0.000187156	−0.000193102	−0.000202700
LEVERAGE		0.150210***	0.118856***
ROA			−0.126746***
R^2	0.500503	0.508130	0.513683
*** , ** and * denote significance at the 1%, 5% and 10%, respectively.			
Year and country fixed effects			

On the other hand, in the model 16 we see significant effects in the sense that CO2 emissions have a positive impact on credit risk, both for small firms, reflected only by the value of l_CO2EMIS, and for large firms, with the latter having a greater impact on credit risk because the coefficient of l_CO2EMIS is added to the coefficient of the l_CO2EMIS*dummyMV variable.

In models 17 and 18, although the effects of emissions on small companies are not significant, we can observe that the credit risk on larger companies is higher if emissions increase.

The result of the p-value in the Wald Test is equal to 0.008, so we conclude that the results obtained in these regressions are significant. Besides, these results are useful to confirm hypothesis number 5 (H5: The effect of carbon emissions on credit risk is higher for larger companies). Indeed, given that the coefficient for the variable l_CO2EMIS*dummyMV is 0,0029 in the model 18, we can confirm that, for a certain level of carbon emissions, the probability of default is between 0.29% higher for larger companies.

6.2 Controlling for emissions and environmental expenditures

In this next section, we include the interaction between carbon emissions and firms' environmental expenditures. This variable will help to control for the effect of carbon emissions when the company presents high or low environmental expenditures, on credit risk, so that we can see whether the probability of default is affected by the level of expenditures.

Table 15 shows the models that will be used. As can be seen, we will relate carbon emissions (l_CO2EMIS) and the level of environmental expenditures (dummyENVEXP, equal to 0 when low, 1 when high) by means of a multiplication.

Table 15. Specific models for environmental expenditures control

MODELS CONTROLLING FOR EMISSIONS AND ENVIRONMENTAL EXPENSES	
19	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2l\_CO2EMIS_{i,t} + \beta 3l\_CO2EMIS_{i,t}{*}dummyENVEXP_{i,t} + \beta 4dummyENVEXP_{i,t} + \beta 5l\_MV_{i,t} + \beta 6BTM_{i,t}$
20	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2l\_CO2EMIS_{i,t} + \beta 3l\_CO2EMIS_{i,t}{*}dummyENVEXP_{i,t} + \beta 4dummyENVEXP_{i,t} + \beta 5l\_MV_{i,t} + \beta 6BTM_{i,t} + \beta 7LEVERAGE_{i,t}$
21	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2l\_CO2EMIS_{i,t} + \beta 3l\_CO2EMIS_{i,t}{*}dummyRNVEXP_{i,t} + \beta 4dummyENVEXP_{i,t} + \beta 5l\_MV_{i,t} + \beta 6BTM_{i,t} + \beta 7LEVERAGE_{i,t} + \beta 8ROA_{i,t}$

Table 16. Results for specific models for controlling for environmental expenditures

	Model 19	Model 20	Model 21
Constant	1.08362***	0.994351***	0.977669***
RC_1	0.0994535***	0.0870579***	0.0982286***
l_CO2EMIS	0.00279703**	0.00265914*	0.00288127*
l_CO2EMIS*dummyENVEXP	0.000132095*	0.000623708	0.000430004
dummyENVEXP	0.0210845	0.0123084	0.0147539
l_MV	−0.0486476***	−0.0461619***	−0.0452511***
BTM	−7.38026e-05	−8.30702e-05	−9.48742e-05
LEVERAGE		0.111689***	0.0982528**
ROA			−0.0539182
R^2	0.524728	0.528316	0.533595
*** , ** and * denote significance at the 1%, 5% and 10%, respectively.			
Year and country fixed effects			

We can only repair to model 19, which shows that the probability of default is higher with a higher level of carbon emissions, and even when firms' environmental expenditures are high. In other words, these results indicate that the effect of carbon emissions on default risk increases by 0.01% if the firm has high environmental expenditures. But, for the other two models, we observe that the effect of carbon emissions is positive and significant only when environmental expenses are low. In any case, we can see that the p-value obtained from the Wald Test is 0.0033, so we can conclude that the results are significant.

This means that we cannot yet confirm our hypothesis number 2 (H2: Environmental expenses by companies reduce their probability of default). Indeed, models results for this case are contradictory, which suggest a further future research on this issue.

6.3 Controlling for emissions and climate initiatives

In the following models we will control for the effect of carbon emissions on credit risk, while analysing whether firms take climate initiatives to mitigate their carbon footprint. As previously done in the moderator models, we will include an interaction variable which will be the multiplication between carbon emissions (l_CO2EMIS) and the variable showing whether the company takes initiatives or not (CLIMATEACT). In this way, we will have the direct effects of carbon emissions on credit risk (l_CO2EMIS), and on the other hand, the effects of these emissions when the company takes climate initiatives (l_CO2EMIS*CLIMATEACT).

Table 17 shows the models to be used in this section.

Table 17. Specific models for climate initiatives control

MODELS CONTROLLING FOR EMISSIONS AND ENVIRONMENTAL INITIATIVES	
22	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2l\_CO2.EMIS_{i,t} + \beta 3l\_CO2EMIS_{i,t}*CLIMATEACT_{i,t} + \beta 4CLIMATEACT_{i,t} + \beta 5l\_MV_{i,t} + \beta 6BTM_{i,t}$
23	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2l\_CO2.EMIS_{i,t} + \beta 3l\_CO2EMIS_{i,t}*CLIMATEACT_{i,t} + \beta 4CLIMATEACT_{i,t} + \beta 5l\_MV_{i,t} + \beta 6BTM_{i,t} + \beta 7LEVERAGE_{i,t}$
24	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 2l\_CO2.EMIS_{i,t} + \beta 3l\_CO2EMIS_{i,t}*CLIMATEACT_{i,t} + \beta 4CLIMATEACT_{i,t} + \beta 5l\_MV_{i,t} + \beta 6BTM_{i,t} + \beta 7LEVERAGE_{i,t} + \beta 8ROA_{i,t}$

The results obtained are significant and confirm hypothesis number 3 (H3: Climate risk mitigation actions reduce the company's credit risk). In fact, we see that the direct effect of emissions on the probability of default is positive, but that the effect of these emissions is reduced when the company presents activities to reduce its carbon footprint.

Furthermore, we can reconfirm that the data are significant, given that the p-value result in the Wald Test is 0.0044, thus highlighting that the sum of the l_CO2EMIS and interaction variables is different from 0.

Table 18. Results for specific models for controlling for climate initiatives

	Model 22	Model 23	Model 24
Constant	1.0388***	0.949831***	0.944920***
RC_1	0.183382***	0.169815***	0.175801***
l_CO2EMIS	0.00873306**	0.00893454**	0.00892724**
l_CO2EMIS*CLIMATEACT	−0.000713132*	−0.000799015*	−0.00106563*
CLIMATEACT	0.0259750	0.0266820	0.0302934
l_MV	−0.0500659***	−0.0476705***	−0.0472195***
BTM	−0.000116802	−0.000124515	−0.000130873
LEVERAGE		0.105888***	0.0950304***
ROA			−0.0449037
R^2	0.534254	0.537963	0.541726
*** , ** and * denote significance at the 1%, 5% and 10%, respectively.			
Year and country fixed effects			

From this section we can conclude that the effect of carbon emissions on the probability of default is 0.07% lower when companies take actions to mitigate their climate effects.

6.4 Controlling for emissions and compensations for executives

Finally, to conclude by studying the moderating effects, we include models in which the interaction is added through a multiplication between the carbon emissions and executive compensation variables. In this way, we can control for the effects of emissions on credit risk when executives are compensated to reduce their carbon footprint.

Table 19 presents the models to be used to control for this effect.

Table 19. Specific models for executive compensations control

MODELS CONTROLLING FOR EMISSIONS AND COMPENSATIONS FOR EXECUTIVES	
25	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 21\_CO2.EMIS_{i,t} + \beta 31\_CO2EMIS_{i,t}{*}COMPEXEC_{i,t} + \beta 4COMPEXEC_{i,t} + \beta 51\_MV_{i,t} + \beta 6BTM_{i,t}$
26	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 21\_CO2.EMIS_{i,t} + \beta 31\_CO2EMIS_{i,t}{*}COMPEXEC_{i,t} + \beta 4COMPEXEC_{i,t} + \beta 51\_MV_{i,t} + \beta 6BTM_{i,t} + \beta 7LEVERAGE_{i,t}$
27	$RC_{i,t} = \beta 0 + \beta 1RC\_1_{i,t-1} + \beta 21\_CO2.EMIS_{i,t} + \beta 31\_CO2EMIS_{i,t}{*}COMPEXEC_{i,t} + \beta 4COMPEXEC_{i,t} + \beta 51\_MV_{i,t} + \beta 6BTM_{i,t} + \beta 7LEVERAGE_{i,t} + \beta 8ROA_{i,t}$

For these models we can also see that the results are significant. In them we can observe that the default risk increases when the level of emissions increases, although the effect of emissions is reduced if the company compensates executives for reducing the company's carbon footprint.

Moreover, the p-value we received in the Wald Test results is 0.0074, so we can conclude that the results obtained in these models are significant.

Table 20. Results for specific models for controlling for executive compensations

	Model 25	Model 26	Model 27
Constant	1.05753***	0.977221***	0.973075***
RC_1	0.186853***	0.174920***	0.181272***
l_CO2EMIS	0.00935382**	0.00953647**	0.00949856*
l_CO2EMIS*COMPEXEC	−0.00201688*	−0.00203103*	−0.00210575*
COMPEXEC	0.0405608	0.0379793	0.0389044
l_MV	−0.0511184***	−0.0489189***	−0.0484507***
BTM	−0.000120779	−0.000128623	−0.000135382
LEVERAGE		0.0953088***	0.0828260***
ROA			−0.0470577
R^2	0.534254	0.537163	0.540875

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.
Year and country fixed effects

As a result, in this case we can confirm hypothesis number 4 (H4: Incentives offered to executives to reduce carbon emission decrease its company's probability of default). Thus, carbon emissions increase the probability of default by 0.093%, although this effect is reduced by 0.02%, to 0.073%, if companies offer their executives rewards for reducing their carbon footprint.

7. ROBUSTNESS TESTS

In this section we perform a robustness test to test the quality and reliability of the main results obtained by the regression models in the sections 5 and 6.

Given the large variations in external factors that directly affected credit risk, such as the coronavirus, the energy crisis or the war in Ukraine, we eliminate the last 3 years that have been affected by these events, in order to check whether the results, compared to the other excluded years, are consistent.

Indeed, these events may influence the perception of firms' credit risk by investors and lenders, for example. Firms operating in particularly hard-hit sectors or in geographic areas exposed to these shocks may have experienced greater concern about their ability to generate cash flow and meet their financial obligations. This could have led to a higher assessment of credit risk by rating agencies and potentially more restricted access to funding in the debt markets.

Therefore, as before, we will first perform a univariate analysis in which we will study the main descriptive statistics, the correlation matrix and the difference of means with respect to credit risk. Then, in a multivariate analysis, we will study model by model the impact of each variable on credit risk, adding control variables in steps.

7.1 Univariate Analysis

The aim of this section is gaining insights about the new panel created, the companies' sample, and their respective variables. Firstly, the main descriptive statistics are computed for the whole sample. Table 21 presents the descriptive for the different model variables.

Table 21. Main descriptive statistics of the new sample

	RC	C02.EMIS	CLIMATEACT	ENVEXP	COMP.EXEC	MV	BTM	LEVERAGE	ROA
MEAN	0,03266	12,98422	0,42046	16,49281	0,23602	21,93319	2,55687	0,06084	0,30563
SD	0,11590	2,66189	0,49377	2,44682	0,42475	1,60295	13,34230	0,06568	0,17100
MIN	0,00000	3,66356	0,00000	7,31322	0,00000	16,90063	-66,74000	-0,35755	0,00000
MEDIAN	0,00000	13,05495	0,00000	16,63689	0,00000	21,95953	1,62000	0,05942	0,30053
MAX	0,97629	18,89229	1,00000	22,49400	1,00000	26,06727	646,71000	0,98847	1,47828

For this case we obtain very similar results to those found in the original database. As we have observed above, we see that there are companies in the database that are in totally opposite situations in terms of their probability of default, as it shows a minimum probability of 0 and a maximum of 0.9762. However, we can note that with the exclusion of these years, the maximum value of credit risk has decreased from 0.99 to 0.97. Furthermore, through the median we identify that most of the companies have a probability closer to 0.

On the other hand, if we look at the CO2.EMIS logarithm data, we can see that the mean and median have almost the same value, and this shows us again that the values of CO2 emissions among the companies are very dispersed. Given the difference between the maximum and minimum value they adopt, we again expect significant differences in credit risk, now also assuming that emissions can have a positive effect on credit risk.

As for environmental expenditures, we can observe that there are companies that have significantly higher environmental expenditures, as we find a great difference between the minimum and the maximum values. However, this may also be due to the assumption commented in the previous sections, that large companies are the ones that emit the most, and at the same time, the ones that compensate the most for these effects.

To conclude with the descriptives, the results show, again, that for the two dummy variables e CLIMATEACT and COMPEXEC, the median is equal to 0 and the mean is less than 0.5, meaning that we find more companies that do not take environmental initiatives or do not compensate their executives for reducing climate impact than those that do.

Then, Table 22 presents the correlation matrix, showing the coefficients for all variables included in the study.

Table 22. Correlation matrix of the new sample

	RC	C02.EMIS	CLIMATEACT	ENVEXP	COMP.EXEC	MV	BTM	LEVERAGE
C02.EMIS	-0.076***							
CLIMATEACT	0.0474**	0.2413***						
ENVEXP	-0.0138	0.7129***	0.2517***					
COMP.EXEC	0.0262	0.1873***	0.1795***	0.2237***				
MV	-0.1577***	0.25***	0.0803***	0.4361***	0.1723***			
BTM	-0.0144	0.0134	-0.0515**	-0.0218	-0.0342	0.0047		
LEVERAGE	-0.2314***	-0.0231	-0.0339	-0.0748**	-0.056**	0.0903***	0.003	
ROA	0.1951***	0.1035***	0.0672***	0.1547***	0.0479**	0.0059	0.0315	-0.1512***

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.

The results obtained in this correlation matrix are very similar to those seen in the original sample, even bearing the same signs. However, as in the original sample, the correlations of the descriptive variables in relation to the credit risk variable again contradict the hypotheses put forward.

Among these results relating credit risk and the explanatory variables, only carbon emissions are significant, which shows a negative relationship, and therefore, credit risk should decrease with emissions; and climate initiatives, which increase credit risk if any type of activity is undertaken to reduce the carbon footprint. Although these results are contradictory, we recall that these effects can be offset by the inclusion of control variables in the model, as shown in the previous sections.

Given the effect that the carbon emissions variable in the first models shown in Section 5 has had on the rest of the explanatory variables, it is worth mentioning the correlations of the explanatory variables in relation to the carbon emissions variable. Again, we see that all correlations are positive and significant at 1%, so to check the true effect of the environmental expenditure, climate initiatives and executive compensation variables on credit risk, we must use the models in which we include the interaction between these variables and carbon emissions.

Finally, to conclude the preliminary analysis, a test of mean differences for credit risk attending to different variables is presented, in which the null and alternative hypotheses tested are, respectively: (H_0) difference of means equals 0, or (H_1) exists difference of means. This study of the difference of means will be useful since it shows if the mean of credit risk changes in the new sample depending on whether the variable studied is higher or lower than its mean. To do so, we use again the dummy that was calculated for the mean differences in the original sample.

Table 23. Difference of means with respect to the dependent variable RC of the new sample

	RC(dummy=1)	RC(dummy=0)	Difference
CO2.EMIS	0,03601	0,04118	-0,00517
CLIMATEACT	0,04388	0,03159	0,01228**
ENVEXP	0,01784	0,03147	−0,01363*
COMP.EXEC	0,04265	0,03479	0,00785
	RC(dummy=1)	RC(dummy=0)	Difference
MV	0,02122	0,03627	−0,01505***
BTM	0,00783	0,04171	−0,03388***
ROA	0,00472	0,06119	−0,05648***
LEVERAGE	0,05270	0,01492	0,03777***

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.

The results obtained in the difference of means are only significant for the CLIMATEACT variables and the logarithm of ENVEXP. The results are quite interesting because, repairing the values of the environmental expenses variable, we see that the mean of the default risk is less when the dummy variable of this descriptive variable takes the value of 1, i.e. the risk is lower when expenses are higher.

These results are very important because with the original sample, the result in the difference in means for this descriptive variable had been the opposite, with credit risk being higher when environmental costs were high. Moreover, in the original sample, this variable was the only one that did not confirm the hypothesis presented, so this result could mean a change in the effect of this variable on credit risk.

On the other hand, we see that, this time, the result for the CLIMATEACT variable is significant, and unfortunately, it shows that the credit risk is higher when the company takes actions to reduce its carbon footprint, as we obtained before for the whole sample.

7.2 Multivariate Analysis

In this section we will present the results of the regression models using the new sample. Given the positive correlation found in the previous section between carbon emissions and the other descriptive variables, the models that will be studied are only those that include, on the one hand, carbon emissions (l_CO2EMIS) and the control variables, and on the other hand, the models that include the interactions between carbon emissions and the descriptive variables of l_ENVEXP, CLIMATEACT and COMPEXEC.

In this way, by studying only these models, we will be able to observe firstly the effect that emissions have directly on the probability of default, and secondly, through the interactions, the true effect of the l_ENVEXP, CLIMATEACT and COMPEXEC variables on carbon emissions and credit risk.

7.2.1 Carbon emissions

These first results shown correspond to the direct effect of carbon emissions on credit risk. Table 24 specifies the coefficients of the effect of the variables on credit risk.

The results obtained for this new sample are the same as those shown for the original sample. Carbon emissions again have a positive coefficient, indicating that credit risk is higher when emissions increase.

Table 24. Results for CO2 emissions specific models of the new sample

	Model 28	Model 29	Model 30
Constant	1.37098***	1.26976***	1.26535***
RC_1	0.208744***	0.189389***	0.189691***
l_CO2EMIS	0.0131056**	0.0122943**	0.0120706**
l_MV	−0.0667304***	−0.0637921***	−0.0630735***
BTM	−0.000164899	−0.000164236	−0.000167473
LEVERAGE		0.149599**	0.134683***
ROA			−0.0806961
R^2	0.531582	0.575077	0.576252

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.
Year and country fixed effects

As a result, we can conclude that results of the original sample are consistent, and that hypothesis H1 is confirmed, meaning that the default risk of a company is higher, the higher its level of carbon emissions. In fact, we can say that, all else being equal, the probability of default of a company increases by 1.2% if its carbon emissions increase by 1 unit.

7.2.2 Controlling for emissions and company size

This second section tests whether the results obtained in the original model controlling for the size effect are consistent. For these, table 25 presents the results of these new models.

Table 25. Results for specific models for firm size control with the new sample

	Model 31	Model 32	Model 33
Constant	0.0160839	−0.0391305	−0.0185018
RC_1	0.260040***	0.228331***	0.227992***
l_CO2EMIS	0.00218351*	0.00157513	0.00145491
l_CO2EMIS*dummyMV	0.0106965**	0.0111751**	0.0115080**
dummyMV	−0.188869***	−0.197223***	−0.198240***
BTM	−0.000236285	−0.000229376	−0.000235661
LEVERAGE		0.210853***	0.176890***
ROA			−0.183605***
R^2	0.531946	0.542639	0.539097

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.
Year and country fixed effects

The results are again consistent, and we can confirm hypothesis H5. Model 31 shows that the effect of carbon emissions on the probability of default is 0.2%, while the effect of emissions from large companies is 1.2% (adding the coefficient of l_CO2EMIS and l_ CO2EMIS*dummyMV), this effect being significantly greater than that of small companies. Moreover, the p-value in the Wald Test, referring to the contrast of the sum of the coefficients of the variables l_CO2EMIS and the interaction l_CO2EMIS*dummyMV, is equal to 0.0129, so we conclude that the results of these models are significant.

On the other hand, although in models 32 and 33 the effect of emissions in small companies is not significant, we can observe that the effect in large companies is 1.1% greater.

Therefore, we can conclude that hypothesis H5: The effect of carbon emissions on credit risk is higher for larger companies is fulfilled, and in fact, that the credit risk for small companies increases by 0.02% if emissions increase by 1 unit, keeping the other variables unchanged; and that the default risk for large companies increases by 1.07% more than for small companies.

7.2.3 Controlling for emissions and environmental expenditures with the new sample

In this next section, we include the interaction between carbon emissions and firms' environmental expenditures. This variable will help to control for the effect of carbon emissions when the company presents high or low environmental expenditures, on credit risk, so that we will prove if the results obtained in the original sample are consistent, which indicate that the probability of default increases when the level of expenditures of a company is high.

The results obtained in these models are very interesting. Although hypothesis 2 could not be confirmed with the models presented in point 6, these data show the opposite.

Table 26. Results for specific models for environmental expenditures control with the new sample

	Model 34	Model 35	Model 36
Constant	1.35560***	1.24900***	1.20842***
RC_1	0.132374***	0.114678***	0.114820***
l_CO2EMIS	0.00451947**	0.00344253**	0.00382712**
l_CO2EMIS*dummyENVEXP	−0.00116608*	−0.000389001*	−0.000659782*
dummyENVEXP	0.0484836	0.0356361	0.0385230
l_MV	−0.0615541***	−0.0581507***	−0.0561196***
BTM	−0.000102740	−0.000102520	−0.000109450
LEVERAGE		0.142434***	0.130109**
ROA			−0.104406
R^2	0.549605	0.553520	0.555148

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.
Year and country fixed effects

The coefficients indicate that credit risk increases if the level of carbon emissions increases. However, the coefficient of the variable l_CO2EMIS*dummyENVEXP shows that the effect of emissions on credit risk is reduced if the company has large environmental expenditures. In fact, we can specify that the credit risk of a firm increases by 0.38% if the firm's carbon emissions increase by one unit, but this effect is reduced to 0.31% if the firm has large environmental expenditures.

The Wald Test indicates that the p-value is 0.00316, so, given that it is less than 0.1, we confirm that the results obtained are significant.

This change in results may be due to the increase in credit risk that could be found during the excluded years, indeed, Byström (2021) confirms that the level of credit risk among US blue chip companies increases in tandem with the spread of the Covid-19 virus. Given that these crisis periods produced several problems in the production chain, a large drop in profits was suffered by many companies, and therefore, a higher risk of bankruptcy. In this way, if companies did not adjust environmental spending levels during that period, the database can relate a high level of credit risk to significant levels of environmental spending.

Thus, we can conclude that hypothesis number 2, H2: Environmental expenses by companies reduce their default risk, is fulfilled.

7.2.4 Controlling for emissions and climate initiatives with the new sample

In the following models we will control for the effect of carbon emissions on credit risk, while analysing whether firms take climate initiatives to mitigate their carbon footprint. Also, we will check if the results obtained in the models with the original sample are consistent, given that the test of means difference in this robustness test showed that credit risk was higher when companies took climate initiatives.

Table 27. Results for specific models for climate initiatives control with the new sample

	Model 37	Model 38	Model 39
Constant	1.31114***	1.21052***	1.20750***
RC_1	0.199943***	0.180782***	0.181022***
l_CO2EMIS	0.0135941**	0.0128051**	0.0128007*
l_CO2EMIS*CLIMATEACT	−0.00341575*	−0.00334854*	−0.00391220*
CLIMATEACT	0.0688428	0.0675231*	0.0747630*
l_MV	−0.0648237***	−0.0619018***	−0.0614142***
BTM	−0.000152738	−0.000152209	−0.000155373
LEVERAGE		0.148469***	0.135673***
ROA			−0.0734073
R^2	0.574348	0.579565	0.580737

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.
Year and country fixed effects

For this case, the result of the p-value in the Wald Test is 0.0889, so we can confirm that the sum of the variables is different from 0 and that the results are significant. Consequently, with the results presented, we can conclude that the results with the original sample are consistent. Carbon emissions again have a positive effect on the probability of default, while this effect is reduced if the company takes initiatives to combat its climate impact.

The results are significant for all three models, so we can conclude that hypothesis 3 (H3: Climate risk mitigation actions reduce the company's credit risk) is fulfilled. Specifically, it can be specified that carbon emissions, by increasing by one unit, increase the probability of default by 1.28%, although this effect is reduced by 0.39% if the company takes actions to reduce its carbon footprint.

7.2.5 Controlling for emissions and compensations for executives with the new sample

Finally, in this section we test whether the results obtained in section 6 are consistent, i.e. whether the effect of emissions on credit risk is indeed reduced if companies compensate their executives for reducing their carbon footprint.

Table 28 shows the results of the models in which these effects are observed.

Table 28. Results for specific models for compensations for executives control with the new sample

	Model 40	Model 41	Model 42
Constant	1.35241***	1.25903***	1.25404***
RC_1	0.208253***	0.190333**	0.190685***
l_CO2EMIS	0.0134346**	0.0128392**	0.0127300**
l_CO2EMIS*COMPEXEC	−0.00416900*	−0.00416548*	−0.00444977*
COMPEXEC	0.0726701**	0.0698451**	0.0741465**
l_MV	−0.0662943***	−0.0636657***	−0.0630080***
BTM	−0.000163004	−0.000163043	−0.000166150
LEVERAGE		0.140288***	0.125920***
ROA			−0.0771324
R^2	0.573016	0.577614	0.578907

*** , ** and * denote significance at the 1%, 5% and 10%, respectively.
Year and country fixed effects

The results are again significant and consistent for this case as well, with a positive direct effect on emissions and a reduction if companies compensate their executives for reducing climate damage.

With this, we can conclude that hypothesis number 4, H4: Incentives offered to executives to reduce carbon emission decrease its company's probability of default, is also fulfilled. More specifically, we can conclude that a company's credit risk increases by 1.27% if the company's emissions increase by one unit, although this effect is reduced by 0.44% if the company compensates its executives for reducing the company's climate impact. In addition, we can confirm the verity of these data, given that the p-value is equal to 0.087 in the Wald Test:

As a result, it can be concluded that all the hypotheses raised at the beginning of this work have been fulfilled.

8. CONCLUSIONS

The objective of this study is to analyse the effect of a company's carbon emissions on its probability of default. This topic was made meaningful by the fact that as companies struggled to recover from the pandemic, some may have recognised the importance of sustainability and climate risk mitigation as part of their long-term strategy. Therefore, this paper focused not only on the direct effect of emissions, but also on whether this new strategy adopted by companies to mitigate climate risks, through environmental expenditures, climate initiatives or executive rewards, would also have an effect on the credit risk of these companies.

This study contributes to the literature on corporate credit risk and climate risk, as there are few studies that can be found on this topic, in fact, most studies relating climate and credit risk are focused on the financial market, and/or on US or Asian markets. Therefore, this study is one of the few that analyses the relationship between climate and corporate credit risk in a European setting.

Starting from a sample of 153 Spanish, French and Italian companies, we find a positive effect between the level of carbon emissions and credit risk, i.e. we can confirm that the probability of a company's default risk increases with a higher amount of carbon emissions. Moreover, controlling the results by firm size, we can also confirm that the effect of emissions on credit risk is higher for large firms, which are, at the same time, those that emit and offset the most.

Furthermore, with the results obtained from the regression models, we can conclude that when firms have high environmental expenditures to offset their climate effects, they reduce the effect of emissions on credit risk. In fact, although in the first models we find that the effect is the opposite, by eliminating the years that produce distortions in credit risk we confirm that the effect of emissions on credit risk is reduced for firms with high environmental expenditures.

Besides, we also find that the effect of emissions on companies' credit risk is lower for those companies that do take initiatives to reduce their carbon footprint. Specifically, we can conclude that the effect of emissions is 0.39% or 0.44% lower for companies that take climate initiatives or compensate their executives for reducing emissions respectively.

As awareness of climate change and sustainability continues to grow, climate risk management and the adoption of sustainable practices are increasingly important for the long-term sustainability of companies, as not taking actions to reduce a company's carbon footprint can increase its credit risk due to a combination of financial, regulatory, reputational and operational factors.

We therefore conclude that climate risk management is not only important for mitigating threats, but also for identifying opportunities and strengthening a company's competitive position. We therefore believe that it is essential for companies to integrate climate risk management into their business strategies and operations to ensure their long-term success

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