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TRABAJO FIN DE GRADO EN ADMINISTRACIÓN Y DIRECCIÓN DE EMPRESAS

ESG POLICIES IN THE BANKING INDUSTRY AND THEIR EFFECTS

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Abstract

With the initiatives that drive society, firms, and financial institutions, among others, towards a greener and more sustainable planet, it is important to consider the effect that these measures and policies have. Specifically, throughout this paper, we focus on banks' ability to incorporate ESG policies and the impact this will exert on their default risk, proxied by two different market-based measures. From a sample of European listed banks, and for the period 2010-2019, a univariate analysis shows that correlation exists between the social pillar and the ESG composite with the probability of default. With multivariate models, it can be concluded that the effect of social and ESG variables is always negative and significant. Besides, interactions have been considered to study whether the effect of ESG scores on default risk varies depending on the level of credit risk or on the bank's size. While the first one gave significant results for the four ESG variables, the second not. In addition, it has been studied whether the environmental awareness of the bank's country moderates the relationship between ESG factors and default risk. Finally, two robustness tests were performed by first changing the Chau-Lau and Sy model by the Bharath and Shumway (2008) model. Secondly, the estimation was carried out in an alternative way, obtaining similar results.

Key words**:** Banking industry, Credit risk, ESG policies, ESG risk.

Resumen

Con las iniciativas que impulsan a la sociedad, las empresas y las instituciones financieras, entre otras, hacia un planeta más verde y sostenible, es importante considerar el efecto que estas medidas y políticas tienen. En concreto, a lo largo de este trabajo, nos centramos en la capacidad de los bancos para incorporar políticas ESG, y el impacto que esto ejercerá sobre su riesgo de impago, aproximado por dos medidas diferentes basadas en datos de mercado. A partir de una muestra de bancos europeos cotizados, y con datos del periodo 2010-2019, un análisis univariante muestra que existe correlación entre el pilar social y el compuesto por ESG con la probabilidad de impago. Con modelos multivariantes, se puede concluir que el efecto de las variables sociales, y ESG es siempre negativo y significativo. Además, se han considerado interacciones para estudiar si el efecto de las puntuaciones ESG sobre el riesgo de impago varía en función del nivel de riesgo crediticio o del tamaño del banco. Mientras que la primera dio resultados significativos para las cuatro variables ESG, la segunda no. Además, se ha estudiado si la conciencia medioambiental del país del banco modera la relación entre los factores ESG y el riesgo de impago. Por último, se realizaron dos pruebas de robustez cambiando primero el modelo de Chau-Lau & Sy por el de Bharath y Shumway (2008). En segundo lugar, se realizó la estimación de una forma alternativa, obteniendo resultados similares.

Palabras clave**:** Sector bancario, Riesgo de crédito, Políticas ESG, Riesgo ESG.

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Abbreviation	*Meaning*
BSM	Black-Scholes-Merton measure
CAR	Capital Adequacy Ratio
CDS	Credit Default Swaps
CRM	Credit Risk Management
DD	Distance to Default
EC	European Commission
EIB	European Investment Bank
EPI	Environmental Performance Index
ESG	Environmental, Social and Governance
EU	European Union
NPL	Nonperforming Loan
PA	Paris Agreement
PCA	Prompt Corrective Action
PD	Probability of Default
PPP	Polluter Pays Principle
SDG	Sustainable Development Goals
UN	United Nations
UNGA	United National General Assembly
WMO	World Meteorological Organization

1. INTRODUCTION

Climate change has been and continues to be a worldwide phenomenon that has impacted every individual's life. The World Meteorological Organization (WMO)'s Report on the State of the Global Climate 2020 provides evidence of this changes; from melting glaciers to adverse meteorological phenomena due to extreme volatile temperatures, from the depth of the oceans to the top of mountains risking animal welfare, leading our ecosystem and urban areas to be devastated (WMO, 2021). So big are being its effects so as to achieve alarming rates, and repercussion in the environment, that calls for transformations both in socio-political and in economic related issues (Nightingale, 2021).

However, are individuals and firms aware of the major impact this entails for society? It seems that awareness is rising due to the adoption of new measures not only by public entities but private ones, too (Pires, 2021). Global warming and carbon neutrality are important challenges that influence societies, and organizations in their daily routines (Chaudhry et al., 2021; Calvet et al., 2022).

These movements towards tackling climate change started already time ago. The year 2015 can be considered a milestone towards climate policy because of the major agreements and strategies adopted. Nevertheless, it should be pointed out that this practice started before but intensified since that year. The UN General Assembly (UNGA) conducted a process that led to the approval of the "2030 Agenda for Sustainable Development and the 17 SDGs (Sustainable Development Goals) as a central axis" (UN Dept. of Economic, Social Affairs, 2022). Moreover, the world leaders at the UN conference adopted the Paris Agreement (PA), which established a long-term plan and attainable goals, that serve as a guideline for all countries to reduce their global greenhouse gas emissions. It is considered "the most significant global climate agreement to date" and reviews every five years the countries' progress and targets (Maizland, 2021; UN, 2022). Besides, the last Nobel Price summit promoted a sustainable movement and called for individuals' urgent action to mitigate the damage we are all producing to the planet. These experts state that next decade is crucial for the planet survival. Transformation and corrective actions are needed and can only be done by societies performing towards common objectives (The Nobel Prize, 2021).

Banks may be playing an important role concerning this topic as are a powerful source of funding, as well as providers of investing services. They can create a path towards the fulfilment of greener policies and can contribute to overcome the climate change challenges. How? With the well-known and current ESG (Environmental, Social and Governance) policies, through which banks are offering investment opportunities for a more sustainable world (Deutsche Bank, Business & Enterprise, 2021). ESG actions care about people's surroundings by promoting only ethical investments, taking care of the environment and society above all (Deutsche Bank, 2021).

As suggested by Chaudhry et al. (2021), if not handling social, financial, and economic systems in an appropriate way, the environmental changes in terms of climate change and carbon neutrality towards a sustainable developed society, will not take place. According to these authors, here is where banks can play an important role as they are one of the key drivers of economic development despite being criticized "as contributors of global warming because of their failure to understand the consequences of their lending processes". As observed, the consideration of these practices is also linked to their reputation, aspect that may encourage them when making decisions or actions.

Firms are also important actors since they have the power to implement measures and disseminate information to the public. For that reason, their character is fundamental to take corrective actions. Since some years ago, companies rely on a new way of investing that is supported by institutional investors. According to Inversis (2018), in 2017, an upward trend was already observed on assets managed under strategies classified as ESG, of which almost ¾ were concentrated in Europe. Specifically, in Spain, this number was multiplied by 5 in the period 2009-2017, offering investors a variety of sustainable asset classes, being equity the most widely used. Additionally, analyzing US data published in the US SIF Trends Report 2020, ESG incorporation, which consists of applying ESG factors to investment analysis and portfolio selection, has experienced a huge increase from 1995. That year was when the US SIF Foundation first measured US sustainable investment. Since 2018, it has reported a 42% increase in managed, reaching $16.6 trillion assets at the beginning of 2020. Social followed by environment and government criterion, was the one holding the largest number of assets in 2020. Nevertheless, the largest percentage increase was experienced by the Environment factor (49%), Governance (40%), and Social (36%), from 2018 till 2020. By using these criteria, investors are able "to identify responsible, well-managed companies that will be resilient over the long-term" (US SIF Foundation, 2020).

Within this context of ESG policies, the European Commission (EC) is also adopting measures to embrace and encourage these new sustainable initiatives that foster economic growth. For instance, updating the European Union banking rules to make banks more resilient, by establishing a package in line with their sustainable finance strategy which mentions the ESG investment to contribute to the green transition (EC Directorate-General for Communication, 2021). Additionally, the European Investment Bank (EIB) has introduced a framework to support projects (energy, transport, agriculture, etc.) and align all their operations to the Paris Agreement goals. This will also ensure that counterparts are moving towards a less carbonized business activity by companies elaborating their alignment plans (EIB, 2022).

Furthermore, the EU Sustainable Finance Action Plan fostered the creation of a Green Bond Standard, led by the EIB in 2007. The purpose was just assigning them to climate change mitigating activities, while incentivizing the investment in sustainable initiatives, ensuring transparency in this long-term oriented perspective (EC Financial Stability, 2020). According to Inversis (2018), the funds of these green and social bonds are exclusively used to finance existing or new green/social projects, which must be aligned with its principles. Besides, BBVA[1] supporting renewable energies and sustainable transport, Iberdrola[2] and Banco Santander[3], have led the issuance of these bonds in Spain.

Overall, the increasing number of regulations to tackle these novelties, leads to a process of transformation not only for entities but the society in general. According to KPMG International (2022), investors are showing more interest in sustainable financial products, leading to changes in market composition, peoples' attitude, and demand for organizations.

Given the rise in society's awareness and concern about climate change, and the need to meet the targets towards a greener planet, it is necessary to analyze how the different economic participants can contribute to this process. For instance, a sign of the growth and importance of ESG policies is the creation of new positions and job titles such as

[1] BBVA's webpage https://www.bbva.com/es/
[2] Iberdrola's webpage https://www.iberdrola.es/
[3] Banco Santander's webpage https://www.bancosantander.es/

ESG Analysts Kell (2018). Besides, according to Allen et al. (2021), there has been an increase in the percentage of investments held in funds that incorporate ESG. Regarding respondents of the ESG Global Survey 2021, 22% already incorporated it in almost all its portfolio and expecting this percentage to rise even more in the next years. Moreover, the number of investors including the role of ESG in the organization's investment strategies is increasing rapidly, moving from a minor thing to be central in almost all actions the organization take, showing the upward trajectory of ESG as an approach. Additionally, highlighting the role of public listed banks by incorporating these factors into their policies. Since the first publication of the ESG concept in the UN report "Who Cares Wins" in 2004 (UN Global Compact Leaders Summit, 2004), the positive trend of these sustainable investments has been constant and unimaginable (Deutsche Bank, 2021). All these facts support the need for change as these practices are expected to remain so helping the transition towards a more environmentally friendly and social ecosystem.

However, these changes may impact firms' structures, in terms of allocation of resources, adoption of new machinery, etc., which at the same time might affect their balance sheet and their ability to fulfill their financial obligations.

Regarding banks, is it really a positive aspect for them the introduction of new policies in terms of default risk? Literature examines the channels through which this transition towards a low-emission economy impacts banks' balance sheets (Huang et al., 2021). While most studies show a positive impact of sustainability over credit risk, decreasing it when incorporating sustainable practices (Friede et al., 2015), as well as environmental practices with papers such as Bauer & Hann (2010), Graham & Maher (2006), Schneider (2011) and Dorfleitner et al. (2019), some others show neutral or even negative effects, such as the findings from Menz (2010).

As can be observed, there exists a contradiction in the literature on the ESG effect on default risk. Nevertheless, these studies have been carried out using different measures of credit risk. For instance, Brogi et al. (2022) uses the Z-score as a measure of credit risk. Al-Quadah et al. (2022) applies the NPL ratio, while Höck et al., 2020 uses the CDS spreads. Furthermore, Bauer & Hann (2010) use three metrics: the cost of debt financing, bond ratings, and long-term issuer's ratings. Schneider (2011) also considers bonds to check differences in environmental performance, while Dorfleitner et al. (2019) use an established credit risk model including corporate social performance scores.

However, the literature has proven the superiority of measures based on market data versus accounting measures, such as Altman's Z (Hillegeist et al., 2004; Gharghori et al., 2006; Abinzano et al., 2020). As for the other measure mentioned above, the NPL ratio, we should bear in mind that it is not a global measure of the bank's default risk, but a measure of the risk of a part of the bank's assets. Therefore, this paper wants to analyze the effect of ESG policies on credit risk, using a measure that includes investors' expectations and not only their past accounting information. Specifically, we will use the Bharath and Shumway (2008) model and an adaptation to the case of banks, following Chau-Lau & Sy (2007).

This way, this paper contributes to the existing literature on developing a framework for studying how these factors influence bank's performance, considering them in the business structure and on credit risk management. Also, by conducting univariate and multivariate analyses using Panel data retrieved from Refinitiv Eikon database to observe the current tendency and relationship between different ESG variables and other indicators such as profitability or bank's value, over credit risk.

The remainder of this paper is organized as follows. Section 2 includes some literature review related to ESG performance, risk, and banks. Section 3 provides the two credit risks measures. Section 4 describes the database and the methodology applied. Section 5 includes a univariate analysis, while section 6 focusses on multivariate analysis with model estimations to observe the ESG effect. Section 7 explains the models robustness. Section 8 concludes the paper.

2. LITERATURE REVIEW

Considering the ESG practices and their effect on credit risk assessment, Brogi et al. (2022) investigate the fact that regulators and investors are increasingly demanding banks to issue loans to "sustainable" borrowers by taking into account ESG in their decision-making. Therefore, this action requires a prior assessment of possible candidates to get financing through a Credit Risk analysis. For that reason, it may be relevant to consider how ESG practices and Credit Risk Management (CRM) are related, and how banks could integrate these factors into their business strategy. The fact that banks are observing an increasing change towards sustainable finance lead us think that there is a need for adaptation.

According to Brogi et al. (2022), financial institutions face a challenge when integrating ESG factors into their strategic planning, but at the same time, it seems to be an opportunity towards sustainable/green lending; “a new form that contributes to the achievement of strong, sustainable, balanced, and inclusive growth, through supporting directly and indirectly the framework of the SDG”. They created an ESG index with the average scores of the three dimensions, and then run regression models to test the impact over credit risk, which is measured by the Z-score. They showed a robust relationship between ESG and Z-score of firms, accepting their hypothesis that ESG-scores and firm credit risk are negatively correlated Brogi et al. (2022).

Al-Quadah et al. (2022) analyze the impact of green policies on non-performing loans (NPL) ratio of UAE banks, finding a reduction of the NPL ratio. This supports the idea that introducing lending options that incentivize sustainable practices has a positive impact, favoring banking entities.

Besides, when incorporating the ESG practices into banks’ strategies, the default risk of organizations should be considered as their business depends on firms’ behavior. For instance, if more environmental policies or regulations are in place, as it is the case nowadays due to the rising damages to the planet, existing literature confirms that companies are more likely to not fulfil their obligations with third parties (Huang et al., 2021).

Furthermore, after the European Union (EU) through the EC took steps to establish a framework aimed at fostering economic growth through sustainable investment, while complying with international agreements (PA, UN 2030 Agenda, SDGs), the interest of researchers on the impact of environmental sustainability on credit risk increased (Höck et al., 2020). By using credit default swap (CDS) spreads as a measure of credit risk, Höck et al. (2020) obtain that those companies that incorporate more sustainable practices have lower credit risk spreads, only if they also have a higher creditworthiness. Otherwise, individuals do not reward organizations, not taking advantage of their sustainable efforts. Therefore, being creditworthiness a key aspect to consider when implementing sustainable criteria in the investment decisions.

According to Höck et al. (2020), there exist four interconnected transmission channels through which the default risk of companies can be negatively affected by a lack of environmental sustainability: first, organizations with lower environmental sustainability have higher regulatory risk because of a higher probability of being fined for not complying with established rules, such as the Polluter-Pays Principle (PPP), and a slower adaptation to upcoming laws, that may increase their default risk. Second, these firms will also face higher stakeholder and reputational risks, due to changes in consumers' perceptions and rising awareness regarding ecological issues so punishing misconducts that, as demonstrated by Bauer & Hann (2010), will have an impact on both, firm value, and default risk. Third, being less environmentally sustainable leads to have greater probability of event risks such as environmental disasters, thus have a negative impact on the creditworthiness of firms and increase default risks. Fourth, companies which participate in environmental practices may be refused by investors because they must integrate these criteria into their investments or demand higher risk compensation. The EU by demanding mandatory disclosure could redirect capital to sustainable companies, increasing the refinancing costs for less sustainable ones that will receive lower ratings so being harder to access funding sources. Overall, the sustainability effort in companies affect the level of creditworthiness and their default risk.

On the other hand, Yan Zhou et al. (2022) offers evidence that not only sustainable investment matters but other factors, such as size and ownership structure. While implementing these policies reduces credit risk for major state-controlled banks, it rises for commercial banks due to information and expertise asymmetries. Besides, Srivisal et al. (2021) supports the idea that "the impact of ESG may depend on different nature or culture markets" as only some may benefit from higher credit ratings if covering ESG factors. Nevertheless, Devalle et al. (2017) find that these practices do have an impact on credit ratings scores. This other perspective supports the fact that there may be other factors influencing this relationship.

Therefore, existing literature confirms possible contradictions about the real effect of incorporating sustainable investment on default risk, and the impact of different levels of creditworthiness.

3. CREDIT RISK MEASURES

As mentioned above, the effect of ESG policies on bank's default risk has already been analyzed in the literature, albeit with measures based on the risk of a portion of the portfolio, such as the NPL ratio (Al-Quadah et al., 2022), or based on accounting data, such as Altman's Z (Brogi et al., 2022).

In this paper we want to analyze the effect of ESG policies on credit risk using a measure of credit risk based on market data, and available not only for larger companies, as it happens in the case of CDS spreads (see Abinzano et al., 2020). Specifically, this section presents two market-based credit risk measures, one specially focused on bank's credit-risk, so being the perfect measure for the analysis, while the other encompasses all firms.

Both are characterized by being market-based measures. Although there exist other classical ones, by considering market information, specially from capital[4] markets, more realistic data is taken since market prices include the rational expectations of investors. They usually plan time-ahead so these prices are forward-looking, being a positive aspect to consider when trying to measure the banks' default risk.

3.1. The Bharath and Shumway (2008) model

The first measure is the Bharath and Shumway (2008) model, which is a simplified version of the Black-Scholes-Merton (BSM) measure. For that reason, first the BSM measure is briefly introduced so to get an overview.

The BSM measure is based on Black & Scholes (1973) and Merton (1974) and gives a probability of default (PD) for a company at any given time. According to the Corporate Finance Institute (2022), the PD is the probability of a borrower or debtor defaulting on loan repayments. Specifically, within financial markets, an asset's PD is the probability that the value of the assets falls below the nominal value of the company's liabilities. Therefore, to compute the PD, the BSM measure considers a company financed with equity and a zero-coupon bond and calculates the probability of the value of the assets of the company being below the face value of debt at its maturity. Due to the fact that the value of the total assets and the volatility of its return are unobservable variables, the probability of default can be obtained using the following two assumptions made by Merton (1974). First, he assumes that the firm's total value follows Geometric Brownian motion[5], as presented in equation (1)

[4] https://corporatefinanceinstitute.com/resources/knowledge/trading-investing/capital-markets/
[5] https://www.sciencedirect.com/topics/computer-science/geometric-brownian-motion

(1) $dV_t = \mu V d_t + \sigma_v V dW$

where V is the total value of the firm, μ is the expected continuously compounded return on V, σ_v is the volatility of firm value and dW is a standard Brownian process. The second assumption established is that the equity[6] of a firm finance by equity and a zero-coupon bond, can be valued as a European call option[7] on the value of the company, with strike price equal to the face value of debt, and with exercise date the maturity date.

Besides, the equity value as a function of the total value of the firm can be explained by the Black and Scholes (1973) option pricing model. Regarding this, Merton (1974) model introduces an equation that represents the firms' equity value as:

(2) $E = V_t \mathcal{N}(d_1) - e^{-r^T} F \mathcal{N}(d_2)$

where E is the market value of the firm's equity, F is the face value of the firm's debt, r is the instantaneous risk-free rate, $\mathcal{N}$ is the cumulative standard normal distribution function. Additionally, the remaining two components, d_1 and d_2, are defined as:

(3) $d_1 = \frac{\ln\frac{V}{F} + (r + 0.5\sigma^2{}_V)T}{\sigma_V \sqrt{T}}$

(4) $d_2 = d_1 - \sigma_V \sqrt{T}$

In order to obtain the expression for the probability of default, we can solve a system of two equations for the value of the firm and its volatility. The first equation is the one given by expressions (2)-(4), and the other one comes from the Itô's lemma[8] (5)

(5) $\sigma_E = \left(\frac{V}{E}\right) \frac{\partial E}{\partial V} \sigma_V$

In the original BSM model is stated that $\frac{\partial E}{\partial V} = \mathcal{N}(d_1)$, so, the firm's volatility and equity are related as shown in equation (6)

(6) $\sigma_E = \left(\frac{V}{E}\right) \mathcal{N}(d_1) \sigma_V$

[6] https://corporatefinanceinstitute.com/resources/knowledge/valuation/what-is-equity-value/
[7] https://corporatefinanceinstitute.com/resources/knowledge/trading-investing/call-option/
[8] https://www.quantstart.com/articles/Itos-Lemma/

Overall, the BSM measure uses two nonlinear equations, (2) and (6), to move the value and volatility of firm's equity to an implied PD. In this way, as the market value of equity declines, the probability of default increases.

The Bharath and Shumway (2008) model is introduced as an alternative to solving equations (2) and (6). It is a simplified measure that tries to find the greatest fit to the BSM model so to give the most accurate results in terms of BSM's probability. Now, the different steps to develop this approximation measure are presented.

Firstly, as equation (7) presents, the market value of each firm's debt (D) is approximated with the face value of its debt (F).

$$(7) \quad \text{naïve D} = \text{F}$$

By doing so, instead of having a non-observable value, the face value is known. Then, the risk of the firm's debt and the equity risk (σ_E) are positively related. Also, it is assumed that when firms are close to default, the debt risk is quite high. Therefore, the volatility of firm's debt (σ_D) can be rewrited as:

$$(8) \quad \text{naïve } \sigma_D = 0.05 + 0.25\sigma_E$$

Combining equations (7)-(8) with the previously ones presented, the total volatility of the firm can be expressed as in equation (9)

$$(9) \quad \text{naïve } \sigma_V = \frac{E}{E+\text{naïve D}}\sigma_E + \frac{\text{naïve D}}{E+\text{naïve D}}\text{naïve}\sigma_D = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05 + 0.25\sigma_E)$$

The next step to develop the Bharath and Shumway (2008) model is considering that the expected return on the firm's assets is equal to the firm's stock return over the previous year. In this way, the uncertainty of unknown values is removed.

$$(10) \quad \text{naïve } \mu = r_{it-1}$$

With equation (10), approximately the same information as provided by the BSM iterative procedure is captured by the naïve estimate, μ, depending on past returns. Therefore, the naïve DD is presented as follows:

$$(11) \quad \text{naïve DD} = \frac{\ln\left[\frac{E+F}{F}\right] + \left(r_{it-1} - 0.5 \text{ naïve } \sigma^2{}_V\right)T}{\text{naïve } \sigma_V\sqrt{T}}$$

Moreover, the naïve probability estimate is presented as:

(12) $$\pi_{\text{naïve}} = \mathcal{N}(-\text{naïve DD})$$

Overall, the firm's PD under the Bharath and Shumway (2008) model as an alternative to the market credit-risk BSM measure, is obtained by applying the following equation (13)

(13) $$P_{def,t} = \mathcal{N}\left(-\frac{\ln\frac{E_t+D_t}{D_t}+\left(r_t-\frac{\sigma^2{}_{A,t}}{2}\right)(T-t)}{\sigma_{A,t}\sqrt{T-t}}\right)$$

with

(14) $$\sigma_{A,t} = \frac{E_t}{E_t+D_t}\sigma_{E,t} + \frac{D_t}{E_t+D_t}\left(0{,}05 + 0{,}25\sigma_{E,t}\right)$$

where $\mathcal{N}$ is the cumulative probability of the Normal (0,1) distribution, E_t is firm's market capitalisation, D_t is the debt nominal value, r_t is the firm's past annual profitability, $\sigma_{E,t}$ is the annual volatility of the stock value, $\sigma_{A,t}$ is an approximation of the volatility of the market value of the firm's total assets, and T is the time to maturity.

To compute the PD, following what written in other papers such as (Crouhy et al., 2000; Vassalou & Xing, 2004; Gharghori et al., 2006), it is assumed that T takes value 1, and the nominal value of debt (D_t) is the sum of short-term debt and half of the long-term debt.

3.2. The Chan-Lau and Sy (2007) model

The Chan-Lau and Sy (2007) model is the main market credit-risk measure applied in this study. While the measure presented in previous section is applied to all firms, the distance-to-capital measure is specially focused on banks, which is also derived as an alternative to the BSM measure.

This is useful because there exist differences between corporate and banks' defaults, as normally, there are actions that proceed bank defaults that make them different (Chau-Lau & Sy, 2007). Moreover, banks should anticipate and take corrective actions if needed in accordance with regulations. To do so, there are some guidelines that provide banks support such as the Basel Committee on Banking Supervision[9]. Furthermore, there is a

[9] https://www.bis.org/bcbs/basel3.htm?m=2572

prompt-corrective-action (PCA) framework that helps identifying and dealing with weak banks before they default. It checks whether they meet solvency requirements based on bank capital levels.

The PCA framework is in charge of recognizing capital thresholds, usually being different values of bank's capital adequacy ratio (CAR), which complement typical default thresholds. As stated in previous empirical papers, the default barrier could be defined as a weighted average of short-term and long-term liabilities, giving a larger weight to the short-term ones. However, within this special framework developed for banks, there is no need to wait until default happens, as the bank intervention or closure may be prompted due to reasons different from asset value being below liabilities. For that reason, (Chau-Lau & Sy, 2007) stated that the default barrier will be consistent with the prevalent PCAR.

To develop the credit-risk measure it is assumed that the assets value of the bank follows a Geometric Brownian motion, so the distance-to-capital is defined as in equation (15).

$$(15) \qquad DC_T = \frac{\ln\frac{V_t}{\lambda L_t} + \left(\mu - \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}$$

where L is the standard default barrier of the bank, defined as the sum of short-term liabilities and half of the long-term ones. Also, λ is a correction factor that depends on the distance measure, which takes a value greater than 1, and is represented by the next formula:

$$(16) \qquad \lambda = \frac{1}{1 - PCAR_i}$$

where $PCAR_I$ is the capital adequacy threshold. According to the Basel Framework[10], first global standard setter for the bank's regulation, the minimum CAR that banks must maintain is 8%. For that reason, this number is taken as PCAR so the PD based on the Chau-Lau & Sy model can be computed as follows:

$$(17) \qquad P_{def,t} = \mathcal{N}\left(-\frac{\ln\frac{E_t + D_t}{\lambda D_t} + \left(r_t - \frac{\sigma^2{}_{A,t}}{2}\right)(T-t)}{\sigma_{A,t}\sqrt{T-t}}\right)$$

[10] https://www.bis.org/basel_framework/

with

$$\sigma_{A,t} = \frac{E_t}{E_t + D_t}\sigma_{E,t} + \frac{D_t}{E_t + D_t}\left(0{,}05 + 0{,}25\sigma_{E,t}\right) \quad (18)$$

Now, these two market-based models can be used to calculate the required values of the credit risk measure, for all the banks in the sample, and the corresponding years.

4. DATABASE AND METHODOLOGY

This section presents the database composed by Eurozone[11] banks, with the different ESG and control variables.

4.1. Database

To analyze whether there is a relationship between the incorporation of ESG policies or measures in the banking sector, and credit risk, market and accounting data have been gathered from Refinitiv Eikon database. Specifically, annual data has been retrieved.

The initial sample included 3,274 banks listed on 66 different country markets. However, this sample was reduced to 557 banks, listed in 51 countries, within and outside Europe. This sample was used to carry out a preliminary analysis to observe how the different variables performed. However, I realized that the legislative framework also played an important role when talking about environmental and social issues. For that reason, the final sample is composed of 341 banks, all of which use the euro as currency, and are listed in 27 different European countries[12]. Thus, despite having a much smaller number of banks in comparison with the initial sample, the results can be considered reliable. This is because Europe is much more homogeneous, and in terms of sustainability, in many cases, the data reported by other countries is little reliable.

Furthermore, the period being analyzed is from 2010 to 2019, being a total of 10 years.

[11] The euro (€) is the official currency of 19 out of 27 EU member countries which together constitute the Eurozone (https://european-union.europa.eu/institutions-law-budget/euro/countries-using-euro_en)
[12] Austria, Belgium, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Lithuania, Luxembourg, Malta, Montenegro, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom

4.2. Methodology

After presenting both market-based credit risk models, this section presents the procedure followed to gather the final sample of 341 banks, as well as the probability of default (PD) by applying the two models' definitions, different indicators, and dummy variables.

Even though the initial sample included 3,274 banks, the database included many banks for which there was not enough data, so it was necessary to clean them. The main aspect considered to include or not a given bank in the final sample, was to have ESG scores for the four pillars (environmental, social, governance and the total ESG), the three individual pillars, and the composite. After considering this aspect, there was a total of 695 banks. Nevertheless, since data on control variables is also needed to perform the analysis, we had to clean up the sample even more. After having done several screens to remove missing values, errors because of downloading the data from the database, and just considering those operating with euro currency, a sample of 557 banks resulted. However, despite using the Euro, some of these banks are also listed in countries outside Europe.

As mentioned above, the legislative framework is important when dealing with environmental and social issues. Indeed, according to the Morningstar Sustainability Atlas (2022), European countries—particularly those in the north—lead the pack in ESG practices around the world. So, in order to have a more homogeneous sample, only those banks listed within the European continent will be considered for the analysis. Nonetheless, there were still some missing values for some years or banks, as well as for certain variables. The issue here is that the sample size already decreased significantly in comparison with the initial number of banks when doing the first debugging. For that reason, another criterion was considered, being sufficient to include a bank in the sample, to have data for the main variables, the four ESG variables and other control variables.

Additionally, and due to the same reason, the period to be analyzed is from 2010 to 2019. Despite having data in the initial database for year 2021, it is not included as data was very scarce for the analysis, therefore being the results not significant. Moreover, year 2020 has been discarded at the very last moment as some results were not significant. This may be due to the fact that the year 2020 was atypical for all industries, so the data may not be fully reliable. For that reason, after considering both and comparing results, only 10 years are presented in the study. Nevertheless, the results obtained with the sample analyzing from the year 2010 to 2020, a period of 11 years, are available upon request from the authors.

Having explained the two market-based models used to calculate the credit risk measure, the probability of default, the procedure used for each of the banks in the sample, and for each year, is now explained.

With the data retrieved from Eikon Refinitiv, we have calculated each of the variables required to compute both, the approximated volatility of market value of firm's total assets, $\sigma_{A,t}$, and the probability of default $P_{def,t}$. This was done first applying the Bharath and Shumway (2008) model, and afterwards, the Chan-Lau and Sy model.

Considering equation (14), first, we calculated the nominal value of debt D_t by adding the short- and half of the long-term value. The market capitalization, E_t, was already given and I only had to consider the value in thousands, and not in million euros. With these two values, I was able to compute the two equation ratios, debt, and equity with respect their sum. Then, with the market value data I computed the past annual profitability r_t. Data from previous years were needed as for instance, for the year 2010, I did the natural logarithm of the ratio of 2009 to 2008. This was done for every year. The next step was to compute the annual volatility of the stock value, σ_e, for which we performed different steps. With the market value data, we computed the natural logarithm from 2006 to 2020. Since we are considering annual data, to calculate the volatility, we took values from the previous five years so as not to contamine the sample too much. Then, we applied the population standard deviation function to get the volatility for each year. Finally, with all these metrics, we were able to apply equation (14) so to get the approximated volatility of market value of firm's total assets, $\sigma_{A,t}$.

This procedure is common to both credit risk models, so we used all the values explained so far to compute both default probabilities.

Now, considering the Bharath and Shumway (2008) model, we computed the ratio, using again the nominal value of debt and the market capitalization. After doing so, we already had all the elements needed to calculate the PD applying equation (13). First, we did the calculation inside the parenthesis, assuming the maturity, T, is equal to one. Then, we computed the normal distribution with mean zero and standard deviation one, obtaining the probability of default.

Under the Chan-Lau and Sy (2007) model, we applied equation (17). The only difference with respect to what has been explained above, is that for computing the ratio using D_t, and E_t, an extra element, λ, which is a correction factor, introduced in equation (16). Afterwards, we were able to verify that by applying the Bharath and Shumway (2008) model, the PD was lower than when calculated under the Chan-Lau and Sy model. It is confirmed that the latter takes into account that banks follow a different policy to measure credit risk, which is more restrictive, being the default probability higher.

Having a sample of banks, the main measure applied throughout the study is the Chan-Lau and Sy'. In this way, we will be able to observe the impact of ESG policies and measures in the banking industry, on credit risk. However, the PD calculated with the Bharath and Shumway (2008) model has also been used for comparative purposes in terms of significance levels, and explanatory variables, as can be seen in section 7.

Additionally, with the data retrieved we computed two more indicators, used as control variables within the models. First, Return on Assets (ROA) as the ratio of earnings before interest and taxes (EBIT) to total assets (TA), which gives information about earnings per unit of assets hold by the bank. Second, the Leverage (L), as the ratio of debt to TA, to measure indebtedness.

Moreover, another indicator, the Environmental Performance Index (EPI) has been included in the study. By considering different performance indicators, it ranks countries on environmental health and ecosystem vitality to taste worldwide sustainability (EPI, 2022). Despite not being included in the Refinitiv Eikon database, we decided to incorporate this data, by combining the scores of this index for the European countries where the banks included in the sample are listed. In this way, it can be tested whether those countries achieving higher scores in the EPI, for each year, have an effect on the PD of those banks listed in that given country.

After managing the retrieved information, computing the credit risk measures and having established the different control variables, a panel data resulted that will be used for conducting a univariate as well as multivariate analysis. Table 1 summarizes the different ESG, and control variables included in the panel, as well as the credit-risk measures and their corresponding definitions. This step was crucial to be able to open the spreadsheet with Gretl[13], software package used for this study. I used it to carry out both, the univariate and bivariate analysis.

Table 1 Panel data variables

Variable	Acronym	Definition
ESG variables		
ENSCORE	E	Refinitiv's Environment Pillar Score is the weighted average relative rating of a company based on the reported social information.
SOSCORE	S	Refinitiv's Social Pillar Score.
CGSCORE	G	Refinitiv's Governance Pillar Score.
ESGSCORE	ESG	Refinitiv's ESG Score is an overall company score based on the self-reported information in the environmental, social, and corporate governance pillars
Control variables		
Total assets	TA	Total assets value indicates the bank size
Market to book value	MTBV	Market to book value is a ratio that helps to understand the market's perception about how the specific firm is performing
Leverage	L	Leverage indicates how bank's increase earnings with a specific level of TA.
Return on assets	ROA	Return on assets shows the percentage of how profitable a firm's assets are in generating profits
Environmental Performance Index	EPI	The EPI provides an overview of the state of sustainability around the world. However, only the countries in this sample have been considered for the study.
Credit Risk Measures		
Bharath and Shumway (2008) Probability of Default	PDbharath	A credit risk measure developed for firms, and which will be the dependent variable of the models for the multivariate analysis
Chan-Lau and Sy Probability of Default	PDchau	A credit risk measure developed specifically for measuring default risk of banks. Also used as dependent variable for the multivariate analysis

This table shows the variables used in the study.

Although the data retrieved from Eikon Refinitiv is already the score for each ESG pillar and ESG composite, it is interesting to know the categories behind. The environmental pillar score comes from three different categories which include emissions, innovation,

[13] http://gretl.sourceforge.net/

and resource use. The Social pillar is based on the community, human rights, product responsibility and workforce categories. Finally, the Governance score comes from Corporate Social Responsibility (CSR) strategy, management, and shareholders inputs (Refinitiv, 2022). In this way, a reliable indicator is provided, capable of measuring a firm's relative ESG performance, commitment, and effectiveness (Refinitiv, 2022).

To carry out the univariate and multivariate analysis, I retrieved additional data to describe and categorize banks. For instance, total assets information as a measure of bank's size. Thus, banks could be classified as large or small banks, with respect to the median. This can be of great interest when running regressions, developing models, and drawing conclusions. Besides, the MTBV is included as control variable. It indicates the current market value of a bank, relative to its book value. Next, the ROA and Leverage are indicators that can be included within the basic model to run regressions and see possible changes in the effects, and significance levels.

Finally, the two most important variables that we have computed as dependent variables of the model. The PD calculated according to the Bharath and Shumway (2008) model, as well as the Chau-Lau and Sy (2007) model. While indebtedness (measured with nominal value of debt) is used to measure the bank's level of debt with third parties, the PD is a credit risk measure that informs about the probability that a given bank will not be able to repay its debts.

Furthermore, several dummy variables have been created for a more meaningful analysis. We used the median for each year as the threshold. For instance, for the year 2010, we took all the data of one variable for that year, calculated the median, and checked whether the value of each bank was above or below. This procedure was followed for each year of the period analyzed, and for each variable.

The dummy variables (see Table 2) are used for two different purposes. First, some were used to perform the tests of variances and means, a univariate analysis, to get a preliminary view. Second, other dummy variables were created with the purpose of introducing them in the regression models to see the effect on bank's default probability.

Table 2: Dummy variables

Variable	Acronym	Definition
Environment Score	Ehigh	It takes value 1 if the environmental score in a specific year is higher than the median of all year's values, and 0 otherwise.

Social Score	Shigh	It takes value 1 if the social score in a specific year is higher than the median of all year's values, and 0 otherwise.
Governance Score	Ghigh	It takes value 1 if the governance score in a specific year is higher than the median of all year's values, and 0 otherwise.
ESG composite Score	ESGhigh	It takes value 1 if the ESG score in a specific year is higher than the median of all year's values, and 0 otherwise.
Market to Book Value	MTBVhigh	It takes value 1 if the MTBV value in a specific year is higher than the median of all year's values, and 0 otherwise.
Return on Assets	ROAhigh	It takes value 1 if the ROA in a specific year is higher than the median of all year's values, and 0 otherwise.
Leverage	Lhigh	It takes value 1 if the leverage in a specific year is higher than the median of all year's values, and 0 otherwise.
Probability of default (Bharath and Shumway)	PDhighB	It takes value 1 if the PD given by Bharath and Shumway (2008) in a specific year is higher than the median of all year's values, and 0 otherwise.
Probability of Default (Chan-Lau and Sy)	PDhighC	It takes value 1 if the PD given by the Chan-Lau and Sy (2007) model in a specific year is higher than the median of all year's values, and 0 otherwise.
Total Assets	TAhigh	It takes value 1 if TA in a specific year is higher than the median of all year's values, and 0 otherwise.
Environmental Performance Index	EPIhigh	To analyze whether there is a relationship between a country's EPI rating and the country where banks are listed, we give value 1 if that country's value, by year, is higher than the median of that year, and 0 otherwise.
Sovereign debt crisis	D_crisis	To analyse whether the years included in the same, during which the impact of the debt crisis was greater, provide significant changes in the results. Giving 1 to years 2010, 2011, and 2012, and 0 otherwise.

The table shows the dummy variables created to first perform the variance and mean contrasts. Second, to be introduced in the regression models as explanatory variables of the dependent variable.

Furthermore, as will be seen in section 6, we have also controlled by year and by country. Therefore, dummy variables have been created and used in the different models. Table 3 presents these dummy variables.

Table 3 Time and country dummy variables

Time dummy variable		**Country dummy variable**			
Year	Variable	Country	Variable	Country	Variable
2010	D1	Austria	D_Austria	Malta	D_Malta
2011	D2	Belgium	D_Belgium	Montenegro	D_Montenegro
2012	D3	Denmark	D_Denmark	Netherlands	D_Netherlands
2013	D4	Estonia	D_Estonia	Norway	D_Norway
2014	D5	Finland	D_Finland	Poland	D_Poland

2015	D6	France	D_France	Portugal	D_Portugal
2016	D7	Germany	D_Germany	Slovakia	D_Slovakia
2017	D8	Greece	D_Greece	Slovenia	D_Slovenia
2018	D9	Hungary	D_Hungary	Spain	D_Spain
2019	D10	Iceland	D_Iceland	Sweden	D_Sweden
		Ireland	D_Ireland	Switzerland	D_Switzerland
		Italy	D_Italy	Turkey	D_Turkey
		Lithuania	D_Lithuania	United Kingdom	D_UK
		Luxembourg	D_Luxembourg		

This table presents the dummy variables created for applying in the multivariate analysis presented in section 6.

Finally, different models have been defined and used, starting from a general one, and then transforming it by including other control variables, as well as dummy variables.

5. UNIVARIATE ANALYSIS

The aim of this section is gaining some first insights about the panel created, the banks sample, and their respective variables. This is done considering the final purpose of the study, which is measuring the effect of ESG on banks' credit risk.

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

For the ESG variables, including the three individuals' pillars, and the ESG composite, it can be noted that all means are similar, around 60 points, being for E the highest. However, this variable is also characterized by having the highest standard deviation, meaning that the E values differ greatly among banks. Moreover, in terms of maximum and minimum values, G achieves the highest value, but with little difference with respect the other three ESG variables. The minimum may not be representative as some banks have zero value for the first years of the analysis (e.g., 2010 and 2011). Lastly, the median is quite relevant as is used as the threshold to compute the dummy variables explained in previous section.

Looking at the last two columns of Table 4, it can be observed the PD calculated with the two different market credit risk models. The maximum and minimum are equal, since being a probability the values go between 0 and 1. Finally, mentioning that for the control variables TA, the variability between banks is significant since differences between maximum and minimum are observed, as well as the standard deviation values are quite large.

Table 4 Main sample descriptive statistics

Statistics	E	S	G	ESG	TA	MTBV	L	ROA	EPI	PDbharath	PDchau
Maximum	97.90	97.58	99.38	94.25	$1.4x10^{12}$	6.530	430.6	0.07545	93.5	1	1
Minimum	0.00	0.65	2.41	1.57	$7.24x10^{6}$	-2.31	0.00	-0.1539	37.25	0	0
Mean	63.63	60.20	58.85	60.01	$1.84x10^{10}$	0.6744	0.5835	0.01094	75.55	0.1703	0.2220
Median	72.63	63.10	62.28	62.34	$5.63x10^{8}$	0.600	0.0370	0.01068	76.4	$1.114x10^{-5}$	0.0001023
Standard deviation	27.76	22.10	23.15	20.39	$9.63x10^{10}$	0.658	9.975	0.01545	7.683	0.3156	0.3608

This table reports the summary statistics for the model variables. E, S, G and ESG values are ratings that go from 0 to 100. TA is in million Euros. MTBV, L and ROA are ratios. EPI is a rating that goes from 0 to 100. Finally, PDbharath and PDchau are probabilities, going from 0 to 1.

Table 5 presents only the mean values of each variable per country. These are the countries where the different banks from the sample are listed.

Table 5 Mean statistic per country

Statistics	Country	E	S	G	ESG	TA	MTBV	L	ROA	EPI	PDbharath	PDchau
	Austria	69.29	61.40	53.69	58.53	$5.02x10^{9}$	0.86	0.09	0.01	78.26	0.23	0.28
	Belgium	58.84	58.53	59.28	57.78	$8.07x10^{9}$	1.12	0.06	0.01	69.82	0.07	0.08
	Denmark	42.74	53.22	50.26	48.87	$6.2x10^{7}$	NA	0.04	0.03	76.77	0.23	0.27
	Estonia	57.26	50.71	63.22	54.73	$4.22x10^{10}$	NA	1.46	0.02	69.58	0.19	0.22
Mean	Finland	80.43	70.53	69.89	70.76	$6.37x10^{8}$	NA	29.50	0.02	77.03	0.29	0.46
	France	65.47	64.46	56.73	60.46	$2.14x10^{10}$	0.63	0.22	0.01	78.17	0.22	0.30
	Germany	62.92	58.89	60.34	58.66	$2.13x10^{10}$	0.44	0.06	0.01	76.86	0.11	0.14
	Greece	64.50	63.07	58.23	60.13	$1.76x10^{8}$	0.30	0.21	0.00	71.13	0.43	0.47
	Hungary	88.55	71.14	54.29	67.17	NA	NA	NA	NA	68.95	0.46	0.48

Iceland	89.15	85.49	88.17	86.58	1.3x10^{9}	NA	0.01	0.01	80.02	0.00	0.00
Ireland	65.65	59.39	58.49	58.58	4.62x10^{8}	1.50	0.22	0.01	73.46	0.19	0.24
Italy	56.73	52.89	52.34	51.71	5.94x10^{9}	0.55	0.18	0.01	75.48	0.20	0.26
Lithuania	45.41	61.59	69.10	59.69	8.55x10^{11}	NA	0.06	NA	69.71	0.31	0.41
Luxembourg	32.19	21.70	18.93	20.31	1.34x10^{8}	NA	0.05	0.01	77.93	0.23	0.27
Malta	56.76	51.55	44.48	48.11	1.35x10^{8}	NA	0.01	0.02	72.04	0.19	0.20
Montenegro	53.04	53.71	55.65	52.99	2.34x10^{11}	0.60	0.14	0.02	64.57	0.30	0.36
Netherlands	75.96	71.67	65.45	69.04	8.39x10^{8}	0.80	0.10	0.01	73.92	0.21	0.24
Norway	78.64	78.92	73.87	75.83	1.27x10^{9}	NA	0.09	0.01	78.51	0.15	0.20
Poland	68.39	66.69	57.54	62.66	9.88x10^{8}	NA	0.07	0.01	68.19	0.15	0.18
Portugal	77.56	70.63	70.57	70.27	2.52x10^{9}	0.69	0.05	0.01	73.08	0.06	0.09
Slovakia	76.87	61.03	53.59	59.35	2.63x10^{9}	NA	0.00	0.01	68.14	0.00	0.00
Slovenia	49.54	55.33	64.67	56.39	5.71x10^{10}	NA	0.12	0.02	74.02	0.26	0.32
Spain	63.46	61.59	62.91	60.85	1.42x10^{9}	0.91	0.10	0.01	75.79	0.11	0.18
Sweden	57.74	56.77	55.60	54.51	1.06x10^{9}	NA	0.07	0.01	83.16	0.10	0.13
Switzerland	52.17	46.13	55.14	48.31	1.56x10^{9}	NA	0.08	0.00	85.18	0.15	0.19
Turkey	70.17	68.71	62.56	65.52	4.64x10^{8}	NA	0.01	0.02	55.76	0.00	0.00
United Kingdom	67.98	60.81	50.03	56.83	5.69x10^{8}	NA	0.11	0.01	77.20	0.24	0.28

This table reports the summary statistics for the model variables. E, S, G and ESG values are ratings that go from 0 to 100. TA is in million Euros. MTBV, L and ROA are ratios. Finally, PDbharath and PDchau are probabilities, going from 0 to 1.

Luxembourg is the country with lowest mean scores for the four ESG variables, while Iceland shows the highest mean values. Besides, most of the country means for the ESG variables are in the 50 to 70 range. Regarding the credit risk measures, again it can be observed that the PDchau values are slightly greater than PDbharath, regardless of the country where the bank is listed. Iceland, Slovakia, and Turkey are characterized by a PD of 0. On the other hand, Hungary, Greece, and Lithuania, have the highest values for the credit risk measures. It is interesting the fact that Iceland, having the highest ESG mean scores, is also characterized by the lowest PD. This could give a first insight about the negative correlation between these variables.

Then, Table 6 presents the correlation matrix, showing the coefficients for all variables included in the study.

Table 6 Correlation matrix

	E	**G**	**S**	**ESG**	**TA**	**MTBV**	**PDbharath**	**PDchau**	**ROA**	**L**
G	0.4391***									
S	0.700***	0.5192***								
ESG	0.7716***	0.7901***	0.9185***							
TA	-0.0718***	0.0974***	0.001	0.025						
MTBV	-0.0209	-0.0413	0.0083	-0.0182	-0.0203					
PDbharath	0.0051	-0.0323	-0.0536***	-0.0417**	0.0859***	-0.2059***				
PDchau	0.0155	-0.0162	-0.0512**	-0.0312	0.0978***	-0.2231***	0.9531***			
ROA	-0.1077***	-0.0124	-0.0327*	-0.0436**	0.1236***	0.0835	0.005	0.017		
L	0.0365*	0.0569***	0.0122	0.0387*	-0.0093	-0.0998*	0.0492**	0.0613***	0.0817***	
EPI	0.0108	0.0024	0.1157***	0.0697***	-0.077***	0.1015*	-0.0394*	-0.0199	0.0116	0.0157

This table shows the correlation coefficients of the different model variables. ***, ** and * denote significance at the 1%, 5% and 10%, respectively.

Considering the ESG variables, it can be observed that the E and G pillars do not affect the credit risk in a univariate way. This is something curious since we would expect a negative and significant relationship between these variables and the credit risk measures. Nevertheless, this will be further analyzed in section d of this paper. Nevertheless, the S pillar, and the ESG composite, reduce the PD, what makes sense. As for banks size, measured through TA, it is given that largest banks, have more G, but less E. Regarding the EPI indicator, those countries achieving a higher score, are also characterized by having greater S, and ESG values, than those achieving a lower score.

These results are striking because, at first glance, not all ESG variables have an effect on credit risk, as not significance is achieved. However, the multivariate analysis will provide another point of view that may explain why this happens.

Finally, to conclude the preliminary analysis, a test of variances and means for different variables is presented. Firstly, a contrast analysis of variances has been carried out by using the test statistic calculator of Gretl, in which the null and alternative hypotheses tested are, respectively: (H_o) the population variances are equal, or (H_1) the population variances are different. Then we performed the test of means differences This is done later since the results obtained from the variance test are needed. On the one hand, 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. For that reason, when computing the contrasts of means, it cannot be assumed that there is a common population standard deviation. On the other hand, if the null is not rejected, then common population standard deviation is assumed for testing whether: (H_o) difference of means equals 0, or (H_1) difference of means.

Table 7 presents the results considering the one-tailed p-value for credit risk, with Chau-Lau and Sy model, depending on whether the value is lower or higher, with respect to the threshold, the median.

Table 7 Contrasts of variances and means

Variable	**Statistic**	**PDchau**		**Difference**
		Low value	High value	
E	Variance	0.13271	0.12757	0.00513
	Mean	0.22354	0.22033	0.00321
S	Variance	0.13802	0.12124	0.01677**
	Mean	0.23243	0.21032	0.02211*
G	Variance	0.13256	0.12804	0.00451
	Mean	0.22659	0.21778	0.00881
ESG	Variance	0.13728	0.12283	0.01445**
	Mean	0.22789	0.21587	0.01202
TA	Variance	0.12017	0.14101	-0.02084***
	Mean	0.19614	0.25413	-0.05799***
MTBV	Variance	0.15772	0.15472	-0.00300
	Mean	0.53428	0.30302	0.23126***
L	Variance	0.05816	0.16402	-0.10585***
	Mean	0.08153	0.37792	-0.29639***
ROA	Variance	0.13399	0.13611	-0.00211
	Mean	0.24343	0.22589	0.01753
EPI	Variance	0.12992	0.10031	-0.00407
	Mean	0.22749	0.21932	0.00817

*This table shows the contrast of variances and means for main model variables. ***, **, and *, indicate the level of significance at 1%, 5% and 10%, respectively.*

This analysis shows that the difference in variances for S, and ESG variables, generate significant results, as well as for control variables such as TA, and L. In the case of mean differences, just the S pillar for the ESG variables, and the same control variables but also the MTBV, provides significant results. It can be assumed that the means are different. These results provide initial information about the sample, and the possible results we may discover in the next section.

6. MULTIVARIATE ANALYSIS

The purpose of this section is presenting and explaining the different models' estimations. For all models the dependent variable is the PD calculated under the Chau-Lau and Sy model (PDchau), as this market credit-risk measure is specific for banks. Specifically, four general models are applied (see Table 8), moving from a basic one which incorporates one constant and two control variables, with the corresponding ESG component, to more complex models. The purpose is analyzing the effect of ESG measures on bank's credit risk.

Table 8 General models

GENERAL MODELS	
1	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1 \mathrm{PDchau}_{i,t-1} + \beta_2 \mathrm{TA}_{i,t} + \beta_3 \mathrm{MTBV}_{i,t} + \beta_4 \mathrm{V}_{i,t}$
2	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1 \mathrm{PDchau}_{i,t-1} + \beta_2 \mathrm{TA}_{i,t} + \beta_3 \mathrm{MTBV}_{i,t} + \beta_4 \mathrm{ROA}_{i,t} + \beta_5 \mathrm{V}_{i,t}$
3	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1 \mathrm{PDchau}_{i,t-1} + \beta_2 \mathrm{TA}_{i,t} + \beta_3 \mathrm{MTBV}_{i,t} + \beta_4 \mathrm{L}_{i,t} + \beta_5 \mathrm{V}_{i,t}$
4	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1 \mathrm{PDchau}_{i,t-1} + \beta_2 \mathrm{TA}_{i,t} + \beta_3 \mathrm{MTBV}_{i,t} + \beta_4 \mathrm{ROA}_{i,t} + \beta_5 \mathrm{L}_{i,t} + \beta_6 \mathrm{V}_{i,t}$

This table shows the four general models applied in the multivariate analysis, going from the basic model 1, to more complex ones which incorporate more control variables.

where $\mathrm{PDchau}_{i,t}$ is the credit-risk measure for bank $_i$ in the period 2010-2019, $\mathrm{PDchau}_{i,t-1}$, is the lagged credit-risk measure for bank $_i$. $\mathrm{TA}_{i,t}$, determines the size of bank i, measured with its total assets value. $\mathrm{MTBV}_{i,t}$, is the ratio measuring the market value of bank $_i$ to its book value, in a given period of time, $_t$. Besides, $\mathrm{ROA}_{i,t}$, determines bank's $_i$ profitability, while $\mathrm{L}_{i,t}$, is a measure of indebtness. Additionally, $\mathrm{V}_{i,t}$, refers to the ESG variable under study. For instance, if analyzing the relationship between the E pillar and PD, this variable will be E. Finally, β_0, is a constant, and $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$, are the corresponding variables coefficients.

Furthermore, after having presented the general models, extra components are incorporated to examine whether the relationship between the control and dependent variables is more or less significant. For this reason, in the following specific models shown in Table 9, the ESG variables are also analyzed one by one, considering the basic structure of models 1 to 4 (see Table 8), but incorporating dummy variables, too.

Table 9 Specific models

SPECIFIC MODELS		
CREDIT RISK	5	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{V}_{i,t} + \beta_4\mathrm{V}_{i,t}PDchau_{i,t}$
	6	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{ROA}_{i,t} + \beta_5\mathrm{V}_{i,t} + \beta_6\mathrm{V}_{i,t}PDchau_{i,t}$
	7	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{L}_{i,t} + \beta_5\mathrm{V}_{i,t}\beta_6\mathrm{V}_{i,t}PDchau_{i,t}$
	8	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{ROA}_{i,t} + \beta_5\mathrm{L}_{i,t} + \beta_6\mathrm{V}_{i,t} + \beta_7\mathrm{V}_{i,t}PDchau_{i,t}$
SIZE	9	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{MTBV}_{i,t} + \beta_3\mathrm{V}_{i,t} + \beta_4\mathrm{V}_{i,t}TAhigh_{i,t} + \beta_5 TAhigh_{i,t}$
	10	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{MTBV}_{i,t} + \beta_3\mathrm{ROA}_{i,t} + \beta_4\mathrm{V}_{i,t} + \beta_5\mathrm{V}_{i,t}TAhigh_{i,t} + \beta_6 TAhigh_{i,t}$
	11	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{MTBV}_{i,t} + \beta_3\mathrm{L}_{i,t} + \beta_4 V_{i,t} + \beta_5\mathrm{V}_{i,t}TAhigh_{i,t} + \beta_6 TAhigh_{i,t}$
	12	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{MTBV}_{i,t} + \beta_3\mathrm{ROA}_{i,t} + \beta_4\mathrm{L}_{i,t} + \beta_5\mathrm{V}_{i,t} + \beta_6\mathrm{V}_{i,t}TAhigh_{i,t} + \beta_7 TAhigh_{i,t}$
EPI	13	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{V}_{i,t} + \beta_5\mathrm{V}_{i,t}EPIhigh_{i,t} + \beta_6 EPIhigh_{i,t}$
	14	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{ROA}_{i,t} + \beta_5\mathrm{V}_{i,t} + \beta_6\mathrm{V}_{i,t}EPIhigh_{i,t} + \beta_7 EPIhigh_{i,t}$
	15	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{L}_{i,t} + \beta_5\mathrm{V}_{i,t} + \beta_6\mathrm{V}_{i,t}EPIhigh_{i,t} + \beta_7 EPIhigh_{i,t}$
	16	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{ROA}_{i,t} + \beta_5\mathrm{L}_{i,t} + \beta_6\mathrm{V}_{i,t} + \beta_7\mathrm{V}_{i,t}EPIhigh_{i,t} + \beta_8 EPIhigh_{i,t}$
CRISIS	17	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{V}_{i,t} + \beta_5\mathrm{V}_{i,t}D\_crisis_{i,t} + \beta_6 D\_crisis_{i,t}$
	18	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{ROA}_{i,t} + \beta_5\mathrm{V}_{i,t} + \beta_6\mathrm{V}_{i,t}D\_crisis_{i,t} + \beta_7 D\_crisis_{i,t}$
	19	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{L}_{i,t} + \beta_5\mathrm{V}_{i,t} + \beta_6\mathrm{V}_{i,t}D\_crisis_{i,t} + \beta_7 D\_crisis_{i,t}$
	20	$\mathrm{PDchau}_{i,t} = \beta_0 + \beta_1\mathrm{PDchau}_{i,t-1} + \beta_2\mathrm{TA}_{i,t} + \beta_3\mathrm{MTBV}_{i,t} + \beta_4\mathrm{ROA}_{i,t} + \beta_5\mathrm{L}_{i,t} + \beta_6\mathrm{V}_{i,t} + \beta_7\mathrm{V}_{i,t}D\_crisis_{i,t} + \beta_8 D\_crisis_{i,t}$

This table shows additional models developed based on the previous models presented in Table 7 and implemented in the study.

To present the different results, I consider the four ESG variables individually while applying all the models presented.

6.1. Environment

This section presents all the models including the Environmental pillar variable, E, under the Chau-Lau and Sy credit-risk model. The results can be seen in the following tables.

Table 10 General models with E and robust (HAC) standard errors

	Model 1				Model 2				Model 3				Model 4			
Cte.	0.858^{***}	0.393^{***}	1.361^{***}	1.653^{***}	0.984^{***}	0.424^{***}	1.559^{***}	1.575^{***}	0.793^{***}	0.375^{***}	1.483^{***}	1.624^{**}	0.898^{***}	0.391^{***}	1.674^{***}	1.475^{**}
Lag	-0.18^{***}	-0.25^{***}	-0.264^{***}	-0.27^{***}	-0.19^{***}	-0.27^{***}	-0.266^{***}	-0.3^{***}	-0.19^{***}	-0.25^{***}	-0.267^{***}	-0.26^{***}	-0.20^{***}	-0.26^{***}	-0.269^{***}	-0.299^{***}
TA	$-4x10^{-10}$	$-3x10^{-10}$ **	$-6x10^{-10}$ ***	$-2x10^{-10}$	$-4x10^{-10}$ **	$-3x10^{-10}$ **	$-6x10^{-10}$ ***	$-1x10^{-10}$	$-4x10^{-10}$ **	$-2x10^{-10}$ **	$-6x10^{-10}$ ***	$-2x10^{-10}$	$-4x10^{-10}$ **	$-2x10^{-10}$ **	$-6x10^{-10}$ ***	$-2x10^{-10}$
MTBV	-0.117^{**}	-0.074^{***}	-0.115^{**}	-0.073^{**}	-0.118^{**}	-0.068^{**}	-0.116^{**}	-0.07^{**}	-0.117^{**}	-0.074^{**}	-0.118^{**}	-0.072^{**}	-0.117^{**}	-0.068^{**}	-0.119^{**}	-0.069^{**}
E	−0.001	0.0001	−0.003	0.0002	−0.003	0.0001	-0.0057^{*}	0.0001	−0.002	$1x10^{-5}$	−0.003	0.0002	−0.004	−0.0001	-0.0059^{*}	0.0002
ROA					1.692	0.819	3.361^{**}	0.051					2.431^{*}	0.891	3.282^{**}	0.084
L									0.5503	0.121	−0.425	0.07	0.821^{**}	0.279	−0.378	0.28
R^2	0.0857	0.5839	0.1535	0.5952	0.1030	0.6284	0.1873	0.643	0.0949	0.5843	0.1556	0.595	0.1226	0.6301	0.1889	0.644
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes

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

According to the results presented above, it can be seen that the E score is not significant when studying the PD of banks. Despite being not significant, it is interesting how the coefficient sign changes from negative to positive when including the time dummy variables in the model. Also, when introducing more control variables, the results do not improve as some variables are significant, but the E remains the same. However, for models 2 and 4, and when the country dummy variable is included, the E provides significant results. Thus, scoring high in the environmental pillar will decrease the PD.

Considering the specific models presented in Table 9, the purpose is to analyze a specific control variable. Specifically, credit risk with the dummy variable (PDhighC), size (TAhigh), EPI (EPIhigh), and the debt crisis (D_crisis). For doing so, we created additional variables as a combination of the corresponding ESG variable, multiplied by one dummy variable, which have been incorporated in the four models. With them, I measured the impact of risk, size, EPI, and the sovereign debt crisis, on the bank's PD.

However, the country dummy variable has not be further considered for these analyses as the results presented above when incorporating these effects were not significant. For that reason, and due to space limit, none or only year dummy variables are included in these specific models. The following tables present the different results.

6.1.1. Credit risk models

Table 11 Credit risk models with E and robust (HAC) standard errors

	Model 5		**Model 6**		**Model 7**		**Model 8**	
Cte.	0.772^{***}	0.391^{***}	0.875^{***}	0.414^{***}	0.713^{***}	0.373^{***}	0.794^{***}	0.381^{***}
Lag	-0.19^{***}	-0.25^{***}	-0.20^{***}	-0.27^{***}	-0.2^{***}	-0.25^{***}	-0.21^{***}	-0.27^{***}
TA	$-3x10^{-10}$	$-2x10^{-10}$ **	$-3x10^{-10*}$	$-3x10^{-10}$ **	$-3x10^{-10}$	$-2x10^{-10}$	$-3x10^{-10\,*}$	$-2x10^{-10}$ **
MTBV	-0.086^{*}	-0.073^{**}	−0.085*	-0.066^{**}	−0.086*	-0.073^{**}	-0.085^{*}	-0.067^{**}
E	-0.0048^{**}	−0.0002	-0.006^{**}	−0.0003	-0.0053^{***}	−0.0003	-0.007^{***}	−0.0006
PDeC	0.0042^{***}	0.0003	0.0044^{***}	0.0006	0.0041^{***}	0.0003	0.004^{***}	0.0006
ROA			1.631	0.822			2.344^{*}	0.893
L					0.505	0.122	0.791^{**}	0.277
R^2	0.1852	0.5844	0.2020	0.6296	0.1929	0.5847	0.2202	0.631
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. PDeC equals E*PDhighC*

In comparison to previous models, when introducing the credit risk dummy variable, significant changes can be observed. Now, the E coefficient is significant, meaning that an increase in the E score, can decrease the default probability of banks. Moreover, for those banks having a PD above the median, an increase will also lead to a higher default probability. Moreover, from the models presented, the 8th one could be the most accurate as all the variables included explain the probability of default at a given level of significance. Despite the lagged PD being negative, it is compensated with the constant term. Nevertheless, when considering time dummies results worsen as the level of significance is lost for the E variable.

6.1.2. Size models

Then, bank size is considered to analyze the effect of E on credit risk. As happened with the first four models, and despite having introduced the total assets dummy variable, the E variable is not significant, so not having effect on the hypothesis.

Table 12 Size models with E and robust (HAC) standard errors

	Model 9		**Model 10**		**Model 11**		**Model 12**	
Cte.	0.66^{***}	0.298^{***}	0.712^{***}	0.272^{**}	0.599^{***}	0.283^{***}	0.625^{***}	0.236^{**}
Lag	-0.18^{***}	-0.25^{***}	-0.19^{***}	-0.26^{***}	-0.19^{***}	-0.24^{***}	-0.20^{***}	-0.25^{***}
MTBV	-0.118^{**}	-0.077^{**}	-0.119^{**}	-0.070^{**}	-0.118^{**}	-0.077^{**}	-0.119^{**}	-0.071^{**}
E	−0.0016	0.0001	−0.0028	0.0001	−0.0021	$-2.7\text{x}10^{-5}$	−0.0038	−0.0002
TAe	−0.011	0.0003	−0.016	0.0032	−0.011	0.0004	−0.015	0.0039
TAhigh	0.950	−0.202	1.623	−0.327	0.978	−0.2	1.509	−0.357
ROA			1.596	0.622			2.333	0.728
L					0.553	0.127	0.808^{**}	0.339
R^2	0.0777	0.5825	0.0954	0.6229	0.087	0.5829	0.1144	0.6255
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. TAe equals E*TAhigh.*

6.1.3. EPI models

Furthermore, the EPI is introduced as a dummy variable in the model. Thus, the aim is to test whether the countries where the banks are listed, and the score they got in this index for each year, have an effect on credit risk.

Table 13 EPI models with E and robust (HAC) standard errors

	Model 13		**Model 14**		**Model 15**		**Model 16**	
Cte.	0.726^{***}	0.414^{***}	0.913^{***}	0.476^{***}	0.612^{***}	0.393^{***}	0.77^{***}	0.433^{***}
Lag	-0.18^{***}	-0.25^{***}	-0.19^{***}	-0.27^{***}	-0.198^{***}	-0.25^{***}	-0.20^{***}	-0.26^{***}

TA	-5x10^{-10***}	-2x10^{-10**}	-5x10^{-10***}	-3x10^{-10**}	-5x10^{-10***}	-2x10^{-10**}	-5x10^{-10***}	-3x10^{-10**}
MTBV	−0.103*	−0.075**	−0.107*	−0.071**	−0.1*	−0.075**	−0.102**	−0.071**
E	−0.001	0.0003	−0.001	0.0007	−0.002	0.0002	−0.002	0.0004
EPIe	0.0006	−0.0007	−0.002	−0.002	0.001	−0.0005	−0.001	−0.0017
EPIhigh	0.145**	−0.009	0.164**	−0.003	0.1595**	−0.006	0.191***	0.004
ROA			1.914	0.867			2.844*	0.943
L					0.688	0.105	1.015**	0.265
R^2	0.1108	0.5841	0.1346	0.6292	0.1247	0.5844	0.1637	0.6307
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. EPIe equals E*EPIhigh.*

Although it makes sense to introduce this indicator in the model, no significant results have been obtained. Therefore, even though the countries where the banks are listed score high in this index, the PD is not affected.

6.1.4. Crisis models

Lastly, a crisis dummy variable has been introduced to see if the fact that certain periods analyzed in this study correspond to years in which the crisis impacted to a large extent the economy, and specifically the banking sector, can have an effect on credit risk.

Table 14 Crisis models with E and robust (HAC) standard errors

	Model 17		Model 18		Model 19		Model 20	
Cte.	0.92***	0.421***	1.054***	0.462***	0.842***	0.404***	0.95***	0.428***
Lag	−0.18***	−0.25**	−0.27***	−0.274***	−0.195***	−0.251***	−0.206***	−0.270***
TA	-5x10^{-10} **	-3x10^{-10} **	-3x10^{-10} **	-3x10^{-10} **	-4x10^{-10} **	-3x10^{-10} **	-4x10^{-10} **	-3x10^{-10} **
MTBV	−0.11**	−0.07**	−0.06**	−0.06**	−0.116**	−0.07**	−0.11**	−0.06**
E	−0.002	−0.0001	−0.0035	−0.0001	−0.002	−0.0002	−0.004	−0.0004
CrisisE	0.0008	0.0003	0.0008	0.0005	0.0006	0.0003	0.0007	0.0005
D_crisis	−0.046	0.093	−0.04	0.076	−0.050	0.092	−0.052	0.07
ROA			1.761	0.582			2.155	0.666
L					0.52	0.103	0.788*	0.267
R^2	0.0901	0.5846	0.1095	0.6296	0.097	0.5848	0.1247	0.6312
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. CrisisE is equal to E*D_crisis.*

Finally, the results show how the E variable is still not significant. Moreover, neither is the crisis variable incorporated.

6.2. Social

This section presents the results obtained when including the Social pillar variable, S, under the Chau-Lau and Sy credit risk model. Next tables show all model’s coefficients.

Table 15 General models with S and robust (HAC) standard errors

	Model 1				Model 2				Model 3				Model 4			
Cte.	1.036***	0.412**	1.06***	1.699**	1.108***	0.453**	1.107***	1.618**	0.955***	0.380	1.139***	1.675**	0.963***	0.385	1.159***	1.521**
Lag	−0.204***	−0.25***	−0.25***	−0.271***	−0.206***	−0.27***	−0.249***	−0.3***	−0.20***	−0.25***	−0.251***	−0.271***	−0.20***	−0.26***	−0.25***	−0.3***
TA	$-3x10^{-10}$ **	$-2x10^{-10}$ *	$-6x10^{-10}$ ***	$-2x10^{-10}$	$-3x10^{-10}$ **	$-3x10^{-10}$ **	$-6x10^{-10}$ ***	$-1x10^{-10}$	$-3x10^{-10}$ **	$-2x10^{-10}$ *	$-6x10^{-10}$ ***	$-2x10^{-10}$	$-4x10^{-10}$ **	$-2x10^{-10}$ *	$-6x10^{-10}$ ***	$-1x10^{-10}$
MTBV	−0.116***	−0.07***	−0.102**	−0.074***	−0.113***	−0.06***	−0.096**	−0.071***	−0.11***	−0.07***	−0.103**	−0.074***	−0.109***	−0.068**	−0.098**	−0.07***
S	−0.0049**	−0.0001	$2x10^{-5}$	−0.0006	−0.0057***	−0.0002	−0.0007	−0.0007	−0.0043*	$-5x10^{-5}$	$-1x10^{-5}$	−0.0006	−0.0048*	$-5x10^{-5}$	−0.0007	−0.0006
ROA					2.199*	0.846	2.671*	0.099					2.415*	0.878	2.616**	0.143
L									0.240	0.120	−0.313	0.061	0.423	0.274	−0.196	0.266
R^2	0.1018	0.5839	0.144	0.5953	0.1207	0.6284	0.1668	0.6438	0.1034	0.584	0.145	0.5953	0.1255	0.6301	0.1673	0.6445
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes

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

Comparing to the E variable, S is significant for the four models presented, when not considering year-fixed effects. The constant term is quite high for all of them, what compensates the negative sign of the lagged credit risk variable. Besides, TA and MTBV show negative coefficients what implies that banks owning more assets and having a greater market value, could result in lower PD. Additionally, when incorporating country fixed effects, the E variable turned to be significant for models 2 and 4, while the S is not. Additionally, the same models used for the E variable are considered now.

6.2.1. Credit risk models

First, incorporating the credit risk dummy variable. The results presented are still significant. While a high S score will lower the PD of banks, those banks with PD being higher than the median value for each corresponding year, will also observe a higher PD due to the positive sign of the PDsC variable. Moreover, the constant terms are still high. When including the ROA or L control variables, the results do not change, basically because these two do not present significant results.

Table 16 Credit risk models with S and robust (HAC) standard errors

	Model 5		**Model 6**		**Model 7**		**Model 8**	
Cte.	0.971^{***}	0.404^{**}	1.039^{***}	0.439^{**}	0.887^{***}	0.373	0.882^{***}	0.372
Lag	-0.212^{***}	-0.25^{***}	-0.22^{***}	-0.27^{***}	-0.21^{***}	-0.25^{***}	-0.22^{***}	-0.27^{***}
TA	$-3x10^{-10}$	$-2x10^{-10*}$	$-3x10^{-10}$	$-3x10^{-10*}$	$-3x10^{-10}$	$-2x10^{-10*}$	$-3x10^{-10}$	$-2x10^{-10*}$
MTBV	-0.091^{**}	-0.074^{***}	-0.088^{**}	-0.068^{**}	-0.089^{**}	-0.074^{***}	-0.084^{**}	-0.067^{**}
S	-0.0084^{***}	-0.0005	-0.009^{***}	-0.0007	-0.007^{***}	-0.0004	-0.0082^{***}	-0.0005
PDsC	0.0045^{***}	0.0005	0.0046^{***}	0.0006	0.0045^{***}	0.0005	0.004^{***}	0.0006
ROA			1.763	0.789			1.993	0.821
L					0.247	0.122	0.455	0.274
R^2	0.1942	0.5847	0.2081	0.629	0.1958	0.585	0.2136	0.631
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. PDsC equals S*PDhighC.*

6.2.2. Size models

Second, the size dummy variable does not present any significant results when measuring the impact of social measures on credit risk. As presented in Table 17, the S variable is still significant, but being classified as larger bank because of the level of total assets being above the median, does not have a special effect on the credit risk of banks.

Table 17 Size models with S and robust (HAC) standard errors

	Model 9		Model 10		Model 11		Model 12	
Cte.	0.876^{***}	0.334	0.885^{***}	0.353	0.787^{***}	0.296	0.731^{***}	0.271
Lag	-0.21^{***}	-0.259^{***}	-0.214^{***}	-0.26^{***}	-0.21^{***}	-0.25^{***}	-0.21^{***}	-0.26^{***}
MTBV	-0.114^{***}	-0.077^{***}	-0.112^{***}	-0.072^{***}	-0.113^{***}	-0.07^{***}	-0.10^{***}	-0.071^{**}
S	-0.0045^{**}	−0.0001	-0.0053^{***}	−0.0008	-0.003^{*}	$3x10^{-5}$	-0.004^{*}	−0.0005
TAs	−0.006	−0.004	−0.006	−0.0013	−0.006	−0.004	−0.007	−0.002
TAhigh	0.374	0.129	0.544	0.08	0.405	0.163	0.585	0.164
ROA			2.108^{*}	0.65			2.317^{*}	0.681
L					0.249	0.154	0.426	0.337
R^2	0.097	0.5838	0.115	0.6233	0.099	0.5843	0.1201	0.6258
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. TAs equals S*TAhigh.*

6.2.3. EPI models

Next, incorporating the EPI does not lead to differences when comparing the results for variable E. The S variable is still having negative coefficients, but the level of significance is reduced to a great extent. Moreover, the EPIs sign is positive, what would mean that those countries achieving a greater score in this index, where the banks are listed, will actually lead to a higher PD. In this case, not being significant leads to better results.

Table 18 EPI models with S and robust (HAC) standard errors

	Model 13		Model 14		Model 15		Model 16	
Cte.	0.97^{***}	0.401^{**}	1.054^{***}	0.438^{**}	0.842^{***}	0.384	0.827^{***}	0.377
Lag	-0.20^{***}	-0.25^{***}	-0.20^{***}	-0.27^{***}	-0.206^{***}	-0.251^{***}	-0.209^{***}	-0.266^{***}
TA	$-4x10^{-10***}$	$-2x10^{-10*}$	$-5x10^{-10***}$	$-3x10^{-10**}$	$-4x10^{-10***}$	$-2x10^{-10*}$	$-5x10^{-10***}$	$-3x10^{-10*}$
MTBV	-0.105^{**}	-0.07^{***}	-0.10^{**}	-0.066^{**}	-0.102^{**}	-0.072^{**}	-0.093^{**}	-0.06^{**}
S	-0.0066^{*}	−0.001	-0.007^{*}	−0.001	−0.005	−0.001	−0.005	−0.001
EPIs	0.003	0.003	0.002	0.003	0.002	0.003	0.002	0.002
EPIhigh	0.139^{**}	−0.018	0.167^{**}	−0.014	0.15^{**}	−0.016	0.19^{***}	−0.005
ROA			2.529^{*}	0.881			2.898^{**}	0.923
L					0.382	0.066	0.669	0.243
R^2	0.1309	0.586	0.1586	0.6302	0.134	0.5861	0.1699	0.631
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

Country-fixed effects	No	No	No	No	No	No	No	No
****, ** and * denote significance at the 1%, 5% and 10%, respectively. EPIs equals S*EPIhigh.*								

6.2.4. Crisis models

Finally, incorporating the dummy variable corresponding to the sovereign debt crisis period, leads to the following results presented in Table 19. The S variable is still significant, but the CrisisS is not. However, looking at the coefficient signs, while an increase in S measures will lead to lower PD, when considering the crisis period, higher values would lead to greater PD, if being significant.

Table 19 Crisis models with S and robust (HAC) standard errors

	Model 17		**Model 18**		**Model 19**		**Model 20**	
Cte.	1.088^{***}	0.418^{**}	1.151^{***}	0.477^{**}	1.003^{***}	0.386	1.011^{***}	0.411
Lag	-0.204^{***}	-0.254^{***}	-0.207^{***}	-0.272^{***}	-0.205^{***}	-0.251^{***}	-0.209^{***}	-0.268^{***}
TA	$-4x10^{-10**}$	$-3x10^{-10*}$	$-4x10^{-10**}$	$-3x10^{-10**}$	$-3x10^{-10*}$	$-2x10^{-10*}$	$-4x10^{-10**}$	$-3x10^{-10**}$
MTBV	-0.117^{***}	-0.074^{***}	-0.111^{***}	-0.068^{***}	-0.117^{***}	-0.074^{***}	-0.111^{***}	-0.068^{**}
S	-0.005^{**}	−0.0002	-0.006^{***}	−0.0005	-0.005^{**}	−0.0001	-0.005^{**}	−0.0003
CrisisS	0.0007	$-7x10^{-5}$	0.00079	0.0002	0.0007	$-6x10^{-5}$	0.0007	0.0002
D_crisis	−0.050	0.117^{**}	−0.045	0.3101^{**}	−0.053	0.115^{**}	−0.053	0.092^{*}
ROA			2.096	0.788			2.202	0.816
L					0.265	0.119	0.443	0.277
R^2	0.1043	0.5839	0.1233	0.6287	0.1060	0.5843	0.128	0.6304
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No
****, ** and * denote significance at the 1%, 5% and 10%, respectively. CrisisS is equal to S*D_crisis.*								

6.3. Governance

This section presents all models under study including the Governance pillar, G, under the Chau-Lau and Sy credit risk measure.

First, the general models are presented in Table 20.

Table 20 General model with G and robust (HAC) standard errors

	Model 1				Model 2				Model 3				Model 4			
Cte.	0.885^{***}	0.315^{***}	1.084^{***}	1.648^{**}	1.030^{***}	0.417^{***}	1.237^{***}	1.578^{***}	0.775^{***}	0.287^{**}	1.156^{***}	1.627^{**}	0.877^{***}	0.357^{**}	1.269^{***}	1.484^{**}
Lag	-0.185^{***}	-0.255^{***}	-0.249^{***}	-0.271^{***}	-0.186^{***}	-0.273^{***}	-0.243^{***}	-0.3^{***}	-0.190^{***}	-0.251^{***}	-0.25^{***}	-0.27^{***}	-0.192^{***}	-0.268^{***}	-0.243^{***}	-0.298^{***}
TA	$-3\times10^{-10\,**}$	$-3\times10^{-10\,**}$	$-6\times10^{-10\,***}$	-2×10^{-10}	$-4\times10^{-10\,**}$	$-3\times10^{-10\,**}$	$-6\times10^{-10\,***}$	-2×10^{-10}	$-4\times10^{-10\,**}$	$-3\times10^{-10\,**}$	$-6\times10^{-10\,***}$	-2×10^{-10}	$-4\times10^{-10\,**}$	$-3\times10^{-10\,**}$	$-5\times10^{-10\,***}$	-2×10^{-10}
MTBV	-0.117^{***}	-0.071^{**}	-0.104^{**}	-0.072^{***}	-0.118^{***}	-0.068^{**}	-0.104^{**}	-0.071^{***}	-0.114^{***}	-0.071^{**}	-0.105^{**}	-0.072^{***}	-0.113^{***}	-0.067^{**}	-0.105^{***}	-0.07^{***}
G	-0.0028^{*}	0.0013	−0.0005	0.0007	-0.0049^{***}	0.00026	−0.0034	−0.0002	−0.0023	0.0013	−0.0004	0.0007	-0.0042^{***}	0.0003	−0.003	−0.0002
ROA					2.333^{*}	0.791	3.02^{**}	0.099					2.673^{*}	0.818	2.978^{**}	0.159
L									0.414	0.131	−0.305	0.055	0.570	0.278	−0.132	0.276
R^2	0.0894	0.5851	0.1442	0.595	0.1136	0.6284	0.1734	0.6436	0.0945	0.585	0.1453	0.5955	0.1232	0.6301	0.1736	0.644
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes

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

It can be observed that G variable is significant for explaining the PD of banks in models 1, 2, and 4, but whenever the year-fixed effects are not introduced. Therefore, the more governance policies introduced, the lower PD will be achieved. Besides, model 2 shows a greater constant value, compensating the negative coefficient of the lagged credit risk measure. When introducing the country-fixed effects, it happens as with the S variable, there are no changes in significance levels. Therefore, G does not explain the PD of banks, but only when no time or country effects are considered.

6.3.1. Credit risk models

Now, the specific models are analyzed. First, the results after introducing the credit risk dummy variable. G remains being significant, and with negative coefficient showing the inverse relationship with respect the dependent variable. It is curious how the sign and the significance level of the coefficient changes when introducing time dummies Besides, the PDgC variable is significant, too. This means that those banks with PD above the median will suffer from a higher PD. Introducing control variables such as ROA or L do not lead to important differences in terms of level of significance or coefficient values.

Table 21 Credit risk models with G and robust (HAC) standard errors

	Model 5		**Model 6**		**Model 7**		**Model 8**	
Cte.	0.837^{***}	0.303^{***}	0.965^{***}	0.394^{***}	0.722^{***}	0.273^{**}	0.804^{***}	0.333^{**}
Lag	-0.194^{***}	-0.259^{***}	-0.199^{***}	-0.280^{***}	-0.199^{***}	-0.256^{***}	-0.205^{***}	-0.276^{***}
TA	$-3x10^{-10}$	$-2x10^{-10**}$	$-3x10^{-10*}$	$-3x10^{-10**}$	$-3x10^{-10}$	$-2x10^{-10**}$	$-3x10^{-10*}$	$-2x10^{-10**}$
MTBV	-0.095^{**}	-0.071^{**}	-0.096^{**}	-0.067^{**}	-0.199^{**}	-0.071^{**}	-0.091^{**}	-0.067^{**}
G	-0.0071^{***}	0.0007	-0.0089^{***}	−0.0004	-0.0066^{***}	0.0007	-0.0082^{***}	−0.0003
PDgC	0.0051^{***}	0.0008^{*}	0.0052^{***}	0.001^{*}	0.0051^{***}	0.0008^{*}	0.0052^{***}	0.001^{*}
ROA			1.798	0.674			2.151	0.701
L					0.434	0.135	0.597^{*}	0.279
R^2	0.1810	0.5866	0.2031	0.6307	0.1867	0.587	0.213	0.632
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. PDgC is equal to G*PDhighC*

6.3.2. Size models

Then, Table 22 shows the results after introducing the TA dummy variable. As happened with the previous ESG variables, considering bank's size as explanatory variable of PD is not significant. If it were, those banks whose total assets value was higher than the median, would suffer from a higher credit risk. However, this cannot be proven.

Table 22 Size models with G and robust (HAC) standard errors

	Model 9		**Model 10**		**Model 11**		**Model 12**	
Cte.	0.734***	0.234**	0.813***	0.266**	0.624***	0.206*	0.657***	0.198
Lag	−0.185***	−0.252***	−0.187***	−0.264***	−0.189***	−0.249***	−0.192***	−0.259***
MTBV	−0.119***	−0.075***	−0.120***	−0.07**	−0.117***	−0.075***	−0.116***	−0.07**
G	−0.003*	0.0011	−0.0055***	0.0003	−0.0027	0.0011	−0.0048***	0.0004
TAg	0.0019	−0.0003	0.003	−0.0007	0.0013	−0.0003	0.0028	−0.0006
TAhigh	−0.222	−0.148	−0.160	0.011	−0.182	−0.14	−0.122	0.0307
ROA			2.43*	0.577			2.743*	0.626
L					0.397	0.139	0.556	0.332
R^2	0.0809	0.5832	0.1032	0.622	0.0856	0.5837	0.1122	0.6254
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. TAg equals G*TAhigh.*

6.3.3. EPI models

Additionally, EPI continues being not significant, although the dummy variable, EPIhigh, is when no time-fixed effects are considered. Moreover, the G variable is only significant when applying model 14.

Table 23 EPI models with G and robust (HAC) standard errors

	Model 13		**Model 14**		**Model 15**		**Model 16**	
Cte.	0.865***	0.318***	1.02***	0.42***	0.704***	0.295**	0.794***	0.359**
Lag	-0.190***	−0.256***	−0.189***	−0.273***	−0.197***	−0.253***	−0.198***	
TA	$-5x10^{-10}$***	$-3x10^{-10}$**	$-5x10^{-10}$***	$-3x10^{-10}$**	$-5x10^{-10}$***	$-2x10^{-10}$**	$-5x10^{-10}$***	$-3x10^{-10}$**
MTBV	-0.110**	−0.071**	−0.108**	−0.067**	−0.106**	−0.071**	−0.1***	−0.066**
G	-0.0017	0.0004	−0.0049*	−0.0003	−0.0004	0.0005	−0.003	$-8x10^{-5}$
EPIg	-0.002	0.0014	−0.0008	0.001	−0.003	0.0012	−0.001	0.0006
EPIhigh	0.157**	−0.014	0.184**	−0.008	0.172***	−0.010	0.21***	0.001
ROA			2.690**	0.835			3.186**	0.865
L					0.598	0.103	0.83*	0.273
R^2	0.1196	0.5856	0.153	0.6286	0.13	0.585	0.1724	0.6302

Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. EPIg equals G*EPIhigh.*

6.3.4. Crisis models

Finally, next Table 24, presents the results after incorporating the crisis dummy variable. This time it is also not representative for explaining the bank's PD. Despite showing positive coefficients for those years in which the crisis had more impact over the economy, in comparison with the negative sign of the G variable, as it is not significant, the effect on PD does not take place.

Table 24 Crisis models with G and robust (HAC) standard errors

	Model 17		**Model 18**		**Model 19**		**Model 20**	
Cte.	0.909^{***}	0.342^{***}	1.057^{***}	0.451^{***}	0.806^{***}	0.318^{**}	0.914^{***}	0.393^{**}
Lag	-0.187^{***}	-0.254^{***}	-0.187^{***}	-0.272^{***}	-0.191^{***}	-0.251^{***}	-0.193^{***}	-0.268^{***}
TA	$-4x10^{-10***}$	$-3x10^{-10**}$	$-5x10^{-10***}$	$-3x10^{-10**}$	$-4x10^{-10**}$	$-3x10^{-10**}$	$-4x10^{-10***}$	$-3x10^{-10**}$
MTBV	-0.111^{***}	-0.069^{**}	-0.109^{***}	-0.065^{**}	-0.112^{***}	-0.069^{**}	-0.11^{***}	-0.065^{**}
G	-0.002^{*}	0.001	-0.0049^{***}	$-4x10^{-5}$	−0.0025	0.0010	-0.0045^{***}	$4x10^{-5}$
CrisisG	0.0007	0.0006	0.0007	0.0008	0.0007	0.0006	0.0006	0.0008
D_crisis	−0.033	0.091^{*}	−0.025	0.074^{**}	−0.037	0.089	−0.033	0.067
ROA			2.471^{*}	0.603			2.59^{*}	0.633
L					0.383	0.106	0.521	0.263
R^2	0.0931	0.5874	0.1189	0.6318	0.0969	0.5876	0.1257	0.6334
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. CrisisG is equal to G*D_crisis.*

6.4. ESG

Finally, this section presents the results after applying all different models including the ESG composite under the Chau-Lau and Sy credit risk model.

Table 25 General model with ESG and robust (HAC) standard errors

	Model 1				Model 2				Model 3				Model 4			
Cte.	1.066^{***}	0.329^{**}	1.069^{***}	1.644^{**}	1.223^{***}	0.411^{**}	1.218^{***}	1.586^{***}	0.965^{***}	0.298	1.145^{***}	1.618^{**}	1.07^{***}	0.346	1.267^{***}	1.491^{**}
Lag	-0.197^{***}	-0.253^{***}	0.249^{***}	-0.27^{***}	-0.199^{***}	-0.272^{***}	-0.246^{***}	-0.3^{***}	-0.199^{***}	-0.250^{***}	-0.25^{***}	-0.269^{***}	-0.201^{***}	-0.268^{***}	-0.246^{***}	-0.299^{***}
TA	$-4x10^{-10}$ **	$-3x10^{-10}$ **	$-6x10^{-10}$ ***	$-2x10^{-10}$	$-3x10^{-10}$ **	$-3x10^{-10}$ **	$-5x10^{-10}$ ***	$-1x10^{-10}$	$-4x10^{-10}$ **	$-3x10^{-10}$ **	$-6x10^{-10}$ ***	$-2x10^{-10}$	$-4x10^{-10}$ **	$-3x10^{-10}$ **	$-5x10^{-10}$ ***	$-2x10^{-10}$
MTBV	-0.122^{***}	-0.072^{***}	-0.103^{**}	-0.073^{***}	-0.122^{***}	-0.067^{**}	-0.102^{**}	-0.071^{***}	-0.119^{***}	-0.072	-0.104^{**}	0.073^{***}	-0.117^{***}	-0.067^{**}	-0.103^{**}	-0.07^{***}
ESG	-0.0055^{***}	0.001	-0.0001	0.0004	-0.0076^{***}	0.0003	-0.003	-0.0002	-0.0048^{**}	0.0011	-0.0001	0.0004	-0.0066^{***}	0.0004	-0.003	-0.0001
ROA					2.615^{**}	0.80	2.862^{**}	0.092					2.809^{**}	0.827	2.808^{**}	0.134
L									0.297	0.130	-0.31	0.066	0.44	0.278	-0.191	0.272
R^2	0.0988	0.584	0.144	0.5952	0.1241	0.6284	0.169	0.6436	0.1013	0.5847	0.145	0.595	0.1295	0.6301	0.169	0.644
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes

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

Observing the results shown in Table 25, it can be stated that the ESG variable has a negative impact on the bank's PD. Four models present a significant level below 5%, so when scoring high in this dimension, the PD decreases. Moreover, all constant values except for model 3 are greater than one, so compensating the negative value of the lagged coefficient. Besides, the ROA variable in models 2 and 4 is significant, while the L variable in models 3 and 4, is not. when incorporating the country dummy variables, it is observable how the effect of ESG is not significant. Therefore, under these four general models, ESG explains the bank's PD when no time or country fixed effects are incorporated.

6.4.1. Credit risk models

Considering the credit risk dummy variable, observing Table 26, not only the ESG variable is significant, but also the PDesgC. Moreover, no differences can be seen across models in the value of the coefficient. Therefore, an increase of one point will lead to an increase in the bank's PD of 0.0048, as this variable indicates the effect when having a PD above the median. The models constant increases when incorporating ROA as control variable, as seen in model 6. Besides, L is not representative. All this is satisfied when no time-fixed effects are included.

Table 26 Credit risk models with ESG and robust (HAC) standard errors

	Model 5		Model 6		Model 7		Model 8	
Cte.	0.998^{***}	0.318^{**}	1.134^{***}	0.384^{**}	0.892^{***}	0.286	0.964^{***}	0.319
Lag	-0.205^{***}	-0.257^{***}	-0.212^{***}	-0.28^{***}	-0.207^{***}	-0.253^{***}	-0.215^{***}	-0.276^{***}
TA	$-3\text{x}10^{-10}$	$-3\text{x}10^{-10**}$	$-3\text{x}10^{-10}$	$-3\text{x}10^{-10**}$	$-3\text{x}10^{-10}$	$-2\text{x}10^{-10**}$	$-3\text{x}10^{-10}$	$-2\text{x}10^{-10**}$
MTBV	-0.0967^{**}	-0.071^{***}	-0.096^{**}	0.067^{**}	-0.094^{**}	-0.071^{**}	-0.091^{**}	-0.066^{**}
ESG	-0.0092^{***}	0.00062	-0.011^{***}	−0.0001	-0.0085^{***}	0.00069	-0.0099^{***}	$-1\text{x}10^{-5}$
PDesgC	0.0048^{***}	0.00064	0.0048^{***}	0.0008	0.0048^{***}	0.00064	0.0049^{***}	0.0008
ROA			2.166^{*}	0.722			2.376^{*}	0.749
L					0.31	0.133	0.483	0.279
R^2	0.1929	0.5853	0.213	0.63	0.1956	0.5857	0.2195	0.6318
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

***, ** *and* * *denote significance at the 1%, 5% and 10%, respectively. PDesg is equal to ESG*PDhighC.*

6.4.2. Size models

Despite having tried with different models that include several control variables, size measured with bank's total assets is not significant when analyzing the effect of ESG policies on credit risk (see results in Table 27).

Table 27 Size models with ESG and robust (HAC) standard errors

	Model 9		**Model 10**		**Model 11**		**Model 12**	
Cte.	0.927***	0.262	1.014***	0.3	0.822***	0.229	0.856***	0.225
Lag	−0.197***	−0.253***	−0.2***	−0.265***	−0.2***	-0.25***	−0.203***	−0.26***
MTBV	−0.122***	−0.0759***	−0.122***	−0.0718***	−0.119***	−0.075***	−0.118***	−0.07**
ESG	−0.0052***	0.00085	−0.007***	−0.0001	−0.004**	0.0009	−0.006***	$-7x10^{-5}$
TAesg	−0.0079	−0.0028	−0.008	−0.0008	−0.008	−0.003	−0.008	−0.001
TAhigh	0.413	0.016	0.587	0.029	0.45	0.044	0.619	0.1
ROA			2.507*	0.639			2.694*	0.672
L					0.296	0.144	0.436	0.335
R^2	0.0931	0.5829	0.1167	0.6228	0.0956	0.5834	0.122	0.6253
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. TAesg equals ESG*TAhigh.*

6.4.3. EPI models

Based on results presented in Table 28, EPI is neither representative as explanatory variable of bank's PD. Even though having tried to include this index in the different models and using as control variable all ESG ones, there is not significance when explaining bank's credit risk.

Table 28 EPI models with ESG and robust (HAC) standard errors

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Cte.	1.033***	0.317*	1.204***	0.398**	0.875***	0.295	0.961***	0.337
Lag	−0.201***	−0.253***	−0.201***	−0.272***	−0.204***	−0.251***	−0.207***	−0.267***
TA	$-4x10^{-10}$***	$-3x10^{-10}$**	$-5x10^{-10}$***	$-3x10^{-10}$**	$-5x10^{-10}$***	$-3x10^{-10}$**	$-5x10^{-10}$***	$-3x10^{-10}$**
MTBV	−0.112**	−0.07**	−0.111**	−0.066**	−0.108**	−0.07**	−0.103**	−0.065**
ESG	−0.0055	−0.0003	−0.0077*	−0.0007	−0.0039	−0.0002	−0.0056	−0.0003
EPIesg	−0.0001	0.0027	−0.0004	0.0022	−0.001	0.0025	−0.0014	0.0017
EPIhigh	0.15**	−0.015	0.178**	−0.011	0.162**	−0.012	0.201***	−0.0013
ROA			2.942**	0.836			3.274**	0.872
L					0.468	0.092	0.705	0.265
R^2	0.1266	0.5853	0.1613	0.629	0.1326	0.5855	0.1744	0.6305

Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. EPIesg equals ESG*EPIhigh.*

6.4.4. Crisis models

Finally, with the crisis dummy variables, the same applies. While the ESG variable is significant and shows an inverse relationship with respect PD, the CrisisESG variable is positive but not significant. Therefore, it cannot be stated that the years during the impact of the sovereign debt crisis affected bank's credit risk in a higher degree.

Table 29 Crisis models with ESG and robust (HAC) standard errors

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Cte.	1.122^{***}	0.363^{**}	1.266^{***}	0.463^{**}	1.025^{***}	0.333	1.122^{***}	0.398^{*}
Lag	-0.197^{***}	-0.252^{***}	-0.200^{***}	-0.272^{**}	-0.2^{***}	-0.49^{***}	-0.203^{***}	-0.268^{***}
TA	$-4x10^{-10**}$	$-3x10^{-10**}$	$-4x10^{-10***}$	$-3x10^{-10**}$	$-4x10^{-10**}$	$-3x10^{-10**}$	$-4x10^{-10**}$	$-3x10^{-10**}$
MTBV	-0.121^{***}	-0.071^{***}	-0.119^{***}	-0.067^{**}	-0.12^{***}	-0.071^{**}	-0.118^{***}	-0.066^{**}
ESG	-0.006^{***}	0.0007	-0.0079^{***}	−0.0001	-0.0055^{***}	0.0007	-0.007^{***}	$-2x10^{-5}$
CrisisESG	0.0009	0.0004	0.0009	0.0006	0.0009	0.0004	0.0009	0.0006
D_crisis	−0.059	0.1^{*}	−0.052	0.079	−0.06	0.098	−0.058	0.071
ROA			2.474^{*}	0.639			2.555	0.667
L					0.298	0.118	0.441	0.276
R^2	0.1026	0.5850	0.128	0.63	0.1049	0.5854	0.1327	0.6318
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

****, ** and * denote significance at the 1%, 5% and 10%, respectively. CrisisESG is equal to ESG*D_crisis.*

7. ROBUSTNESS TESTS

The purpose of this section is to test if the previous results are sensible to the measure of credit risk and the assumption of robust standard errors.

7.1. Change in the credit-risk measure

Despite having used the bank's credit-risk model, the multivariate analysis has also been solved by applying as dependent variable, the PD calculated with the Bharath and Shumway (2008) model. The main reason for that is to not be subject to the credit risk measure developed for banks but using the general market measure, also presented in section 3. Despite obtaining similar results, the following tables show the coefficients and their corresponding significance level for the 4 general models presented in Table 8. Although having applied all twenty models, results available upon request from the authors, only these ones are presented in the study to fit the established number of sheets.

Table 30 General models with E and Bharath and Shumway (2008) model

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Cte.	0.777***	0.293**	0.894***	0.305*	0.715***	0.275*	0.813***	0.274*
Lag	−0.191***	−0.246***	−0.206***	−0.279***	−0.199***	−0.243***	−0.216***	−0.276***
TA	-4x10^{-10**}	-2x10^{-10*}	-4x10^{-10**}	-2x10^{-10*}	-4x10^{-10**}	-2x10^{-10*}	-4x10^{-10**}	-2x10^{-10*}
MTBV	−0.100**	−0.063**	−0.101**	−0.058*	−0.100**	−0.064*	−0.100**	−0.059*
E	−0.0016	0.00017	−0.002	0.00036	−0.0021	-8.1x10^{-5}	−0.0038	0.0001
ROA			1.635	0.816			2.331	0.883
L					0.516	0.127	0.776**	0.262
R^2	0.0836	0.5612	0.1053	0.6120	0.0921	0.5616	0.1239	0.6136
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No
***, ** *and* * *denote significance at the 1%, 5% and 10%, respectively.*								

Under the Bharath and Shumway (2008) model, the E variable is also no significant. Therefore, no changes in comparison with the results presented in the previous section.

Table 31 General models with S and Bharath and Shumway (2008) model

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Cte.	0.966***	0.34*	1.038***	0.38*	0.895***	0.308	0.907***	0.317
Lag	−0.209***	−0.247***	−0.221***	−0.28***	−0.210***	−0.244***	−0.22***	−0.27***
TA	-3x10^{-10**}	-2x10^{-10}	-4x10^{-10**}	-2x10^{-10}	-3x10^{-10**}	-2x10^{-10}	-3.9x10^{-10**}	-2x10^{-10}
MTBV	−0.099**	−0.065**	−0.097**	−0.06**	−0.098**	−0.065**	−0.094**	−0.06**
S	−0.0049**	−0.0004	−0.0057***	−0.0006	−0.0044*	−0.0003	−0.0049**	−0.0004
ROA			2.158	0.887			2.352*	0.916
L					0.208	0.122	0.384	0.259
R^2	0.1010	0.5613	0.1252	0.6121	0.1022	0.5617	0.1294	0.6137

Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No
***, ** *and* * *denote significance at the 1%, 5% and 10%, respectively.*								

The S variable is also significant, as it was under the Chau-Lau and Sy credit risk model. However, changes in the significance level can be seen for model 4, in which this measure provides a higher level of significance. Nevertheless, the constant values, and the S coefficients, are lower when applying this second model.

Table 32 General models with G and Bharath and Shumway (2008) model

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Cte.	0.827^{***}	0.24^{**}	0.971^{***}	0.333^{**}	0.726^{***}	0.21	0.828^{***}	0.275^{*}
Lag	-0.191^{***}	-0.247^{***}	-0.199^{***}	-0.279^{***}	-0.195^{***}	-0.243^{***}	-0.205^{***}	-0.276^{***}
TA	$-3x10^{-10\ **}$	$-2x10^{-10\ *}$	$-4x10^{-10\ **}$	$-2x10^{-10\ *}$	$-4x10^{-10\ **}$	$-2x10^{-10\ *}$	$-4x10^{-10\ **}$	$-2x10^{-10\ *}$
MTBV	-0.101^{**}	-0.062^{**}	-0.102^{**}	-0.059^{**}	-0.099^{**}	-0.062^{**}	-0.098^{**}	-0.059^{**}
G	-0.0029^{*}	0.0010	-0.005^{***}	$3x10^{-6}$	-0.002^{*}	0.0010	-0.004^{***}	$9x10^{-5}$
ROA			2.326	0.856			2.639	0.88
L					0.378	0.137	0.529	0.266
R^2	0.0889	0.562	0.1191	0.611	0.0934	0.562	0.127	0.6136
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No
***, ** *and* * *denote significance at the 1%, 5% and 10%, respectively.*								

According to Table 32, the G variable is also representative when explaining bank's PD. The levels of significance are the same as under the other model, but not for model 3 in which the G variable is not significant. However, the coefficient values are higher under the Chau-Lau and Sy credit risk measure, as well as the constant coefficients.

Table 33 General models with ESG and Bharath and Shumway (2008) model

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Cte.	1.003^{***}	0.265	1.157^{***}	0.339^{*}	0.914^{***}	0.233	1.017^{***}	0.277
Lag	-0.203^{***}	-0.246^{***}	-0.212^{***}	-0.279^{***}	-0.204^{***}	-0.243^{***}	-0.215^{***}	-0.276^{***}
TA	$-3x10^{-10**}$	$-2x10^{-10*}$	$-3x10^{-10**}$	$-2x10^{-10*}$	$-3x10^{-10**}$	$-2x10^{-10*}$	$-4x10^{-10**}$	$-2x10^{-10*}$
MTBV	-0.106^{***}	-0.063^{**}	-0.106^{***}	-0.059^{**}	-0.103^{***}	-0.063^{**}	-0.102^{***}	-0.059^{**}

ESG	−0.0056***	0.00062	−0.0077***	$-7x10^{-5}$	−0.0049**	0.0007	−0.0068***	$-6x10^{-5}$
ROA			2.586*	0.864			2.760*	0.889
L					0.261	0.134	0.399	0.266
R^2	0.0985	0.5613	0.1293	0.6119	0.1005	0.5618	0.1340	0.6136
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

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

Finally, for the ESG variable the levels of significance are exactly the same. Therefore, slight differences can be observed when comparing the results under both market-based credit risk models. This could be helpful when recommending tools for measuring firm's or bank's credit risk.

7.2. Change in the estimation

The next tables show the results obtained for the four general models but without considering the robust standard errors, also applying the Chau-Lau and Sy (2007) model.

Table 34 General models with E and without robust standard errors

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Cte.	0.858***	0.393***	0.984***	0.424***	0.793***	0.375**	0.898***	0.391**
Lag	−0.187***	−0.254***	−0.193***	−0.272***	−0.195***	−0.251***	−0.204***	−0.268***
TA	$-4x10^{-10*}$	$-3x10^{-10*}$	$-4x10^{-10*}$	$-3x10^{-10*}$	$-4x10^{-10*}$	$-2x10^{-10}$	$-4x10^{-10*}$	$-2x10^{-10*}$
MTBV	−0.117***	−0.074**	−0.118***	−0.068**	−0.117***	−0.074**	−0.117***	−0.068**
E	−0.0018	0.0001	−0.0030	0.00013	−0.0023	$1x10^{-5}$	−0.0041*	−0.0001
ROA			1.692	0.819			2.431	0.891
L					0.550	0.121	0.821**	0.279
R^2	0.0857	0.5839	0.1030	0.6284	0.0949	0.5843	0.1226	0.6301
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

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

According to Table 34, the E variable is significant when not introducing the robust standard errors, but only when using model 4. This makes a difference when comparing to the results presented in section 6, as this variable was not significant.

Table 35 General models with S and without robust standard errors

	Model 1		**Model 2**		**Model 3**		**Model 4**	

Cte.	1.036^{***}	0.412^{**}	1.108^{***}	0.453^{***}	0.955^{***}	0.38^{**}	0.963^{***}	0.385^{**}
Lag	-0.204^{***}	-0.254^{***}	-0.206^{***}	-0.273^{***}	-0.204^{***}	-0.251^{***}	-0.207^{***}	-0.268^{***}
TA	$-3.8x10^{-10}$	$-2x10^{-10}$	$-3.8x10^{-10}$	$-3x10^{-10*}$	$-3.8x10^{-10}$	$-2x10^{-10}$	$-3.9x10^{-10}$	$-2x10^{-10}$
MTBV	-0.116^{***}	-0.074^{***}	-0.113^{***}	-0.068^{**}	-0.114^{***}	-0.074^{**}	-0.109^{***}	-0.068^{**}
S	-0.0049^{**}	-0.0001	-0.0057^{**}	-0.0002	-0.0043^{*}	$-5x10^{-5}$	-0.0048^{**}	$-5x10^{-5}$
ROA			2.199	0.846			2.415	0.878
L					0.240	0.12	0.423	0.274
R^2	0.1018	0.5839	0.1207	0.6284	0.1034	0.5843	0.125	0.6301
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

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

Moving to the S variable, it is significant for all four models presented, although the significance level differs if comparing the results shown in Table 15. For instance, for model 2 is lower, but for model 4 is greater.

Table 36 General models with G and without robust standard errors

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Cte.	0.885^{***}	0.315^{**}	1.030^{***}	0.417^{***}	0.775^{***}	0.287^{*}	0.877^{***}	0.357^{**}
Lag	-0.185^{***}	0.255^{***}	-0.186^{***}	-0.273^{***}	-0.190^{***}	-0.251^{***}	-0.192^{***}	-0.268^{***}
TA	$-4.2x10^{-10*}$	$-3x10^{-10*}$	$-4.3x10^{-10*}$	$-3x10^{-10*}$	$-4.2x10^{-10*}$	$-2x10^{-10*}$	$-4.3x10^{-10*}$	$-2x10^{-10*}$
MTBV	-0.117^{***}	-0.071^{**}	-0.118^{***}	-0.068^{**}	-0.114^{***}	-0.071^{**}	-0.113^{***}	-0.067^{**}
G	-0.0028	0.0013	-0.0049^{**}	0.0002	-0.0023	0.0013	-0.0042^{*}	0.0003
ROA			2.333	0.791			2.673^{*}	0.818
L					0.414	0.131	0.570	0.278
R^2	0.0894	0.5851	0.1136	0.6284	0.0945	0.5855	0.1232	0.6301
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

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

Next, the level of significance when looking at the G variable decreases when no robust standard errors are included. It can be seen than when introducing the ROA as control variable, the G variable explains the bank's PD. However, when introducing L, it is not.

Besides, in comparison with results presented in Table 20, the constant values are exactly the same.

Table 37 General models with ESG and without robust standard errors

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Cte.	1.066^{***}	0.329^{*}	1.223^{***}	0.411^{**}	0.965^{***}	0.298	1.07^{***}	0.346^{*}
Lag	-0.197^{***}	-0.253^{***}	-0.199^{***}	-0.272^{***}	-0.199^{***}	-0.25^{***}	-0.201^{***}	-0.268^{***}
TA	$-4x10^{-10}$	$-3x10^{-10}$	$-4x10^{-10}$	$-3x10^{-10}$	$-4x10^{-10}$	$-3x10^{-10}$	$-4x10^{-10}$	$-3x10^{-10}$
MTBV	-0.122^{***}	-0.072^{**}	-0.122^{***}	-0.067^{**}	-0.119^{***}	-0.072^{**}	-0.117^{***}	-0.067^{*}
ESG	-0.0055^{**}	0.0010	-0.0076^{***}	0.0003	-0.0048^{*}	0.0011	-0.0066^{**}	0.00049
ROA			2.615^{*}	0.8			2.809^{*}	0.827
L					0.297	0.13	0.44	0.278
R^2	0.0988	0.5843	0.1241	0.6284	0.1013	0.5847	0.1295	0.6301
Year-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Country-fixed effects	No	No	No	No	No	No	No	No

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

Finally, ESG explains the credit risk of bank's regardless of robust standard erros have been included in the regression models or not. Besides, MTBV and ROA control variables are significant, while TA and L are not. In comparison with the results shown in Table 25, the level of significance is lower, and the TA turns from being an explanatory variable to not being significant. Nevertheless, the constant terms do not differ.

8. CONCLUSIONS

The aim of this study is to review existing literature on the role of banks when moving towards a more sustainable and greener environment. Through sustainable lending and new financing portfolios that contribute to an eco-friendlier development, banks are also affected, so questioning their ability to meet their obligations. Nevertheless, this sustainable transition is being a current topic in the economy and affected not only because of the introduction of new regulations by public institutions, but also because of consumers purchasing decisions. For that reason, we found relevant to analyze the impact that incorporating these new measures and initiatives on banks' structures will have on their credit risk.

This study has contributed to the literature on bank's credit risk and ESG policies, by conducting a univariate as well as multivariate analysis on how the different ESG pillars and control variables explain the banks' default risk. This risk has been measured through the probability of default computed by applying two different market-based credit risk models. On the one hand, the Chan-Lau & Sy (2007) model, which gives a specific measure for banks. On the other hand, the Bharath and Shumway (2008) model, measure that can be applied for any given firm. Thus, results have been compared, with similar conclusions.

Starting from a sample of 341 European banks, we find that the effect of social and ESG variables is always negative and significant, that is, scoring high on these attributes reduces the bank's PD. Then, G varies across models, and the E variable is representative on fewer occasions. When adding time, country, or both, fixed effects, the level of significance of ESG variables is not improved, although it is for E variable under two of the general models. The other variables move from being significant, so explaining the PD of banks, to not explaining the effects over credit risk.

Furthermore, some interactions have been taken into account. Specific models were introduced by including dummy variables into the models. Specifically, we study if the effect of ESG scores on default risk varies depending on the level of credit risk or on the bank's size. While the first one gave significant results for the four ESG variables considered, the second not. Besides, we have also studied the effect of the environmental awareness of the country in which the bank is located to see whether the effect of ESG policies is greater or lesser on bank's credit risk. For this purpose, the EPI score per country has been considered without obtaining significant results. Finally, a dummy of crisis was introduced, considering the period 2010-2012 as the most affected by the sovereign debt crisis, which also lead to not significant results.

Finally, two robustness tests were performed by first changing the Chau-Lau and Sy model by the Bharath and Shumway (2008) model. Results show small deviations, not implying changes in significance levels. Second, the general models were applied without considering the robust standard errors, which neither produced significant differences.

To conclude, I would like to include a personal thought about the work done performing this study as final degree project. It has been challenging as well as intriguing. Despite reporting results, they never come out at first, so being a task that requires great effort, in which small details make a big difference.

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