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Business model and ESG pillars: The impacts on banking default risk

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ABSTRACT

The recent banks' failures have highlighted the importance of improving banking sector supervision, emphasizing the need to adopt a holistic approach to risk assessment based on an evaluation of a bank's business model (BBM) that combines financial (e.g., bank's balance data) and non-financial information (e.g., bank's ESG performance). In this study, we explore the joint effect of BBM and their environmental (ENV), social (SOC), and governance (GOV) pillars performance on banks' riskiness profile. The study uses a sample of 639 EU banks from 2013 to 2022 and applied a random effects model. Our findings suggest wholesale and retail banks could mitigate default risk, enhancing their ENV pillar performance. Differently, investment banks are encouraged to improve their governance best practices and structure to take advantage in terms of riskiness reduction. These results remain consistent after a series of robustness tests, including the 2SLS model and the Arellano coefficient estimation. Our paper offers practical implications for banking supervisory authorities and practitioners, encouraging to adopt a diversified ESG investment strategy according to bank-specific business models.

1. Introduction

Since the end of the financial crisis, supervisory authorities and policymakers have strengthened banking regulation to assess and monitor the vulnerabilities that have affected the financial system (FSB, 2023). Following these regulatory requirements, the bank business model (BBM) has been a topic of interest in the banking literature to understand better business models characteristics and their divergent impact on performance, efficiency, riskiness, and solvency (BIS, 2022). To stress the importance of business model analysis (BMA), some scholars have shown how business models (BMs) contain information that extends beyond the traditional indicators of bank risk and return, providing regulators and supervisors with better insights into the sustainability of bank profits and stability (Lartey, James, Danso, & Boateng, 2022). Focusing on the risk side, some authors (Marques-Ibanez & Scheicher, 2010) have highlighted how business models can signal a firm's risk-taking propensity, facilitating incentives to hedge risk.

The recent medium-size banks' demises (e.g., the SVB bank crisis) have also emphasised the importance of BMA and converging on a compressive evaluation of financial stability. Consequently, supervisory authorities encourage implementing a holistic approach to bank risk assessment to minimize these adverse events and contagion effects in the banking industry (BIS, 2019). Given the evolving market and business environments, supervisors do not look solely at capital adequacy at a single point in time, but rather, they assess BBM viability on longer time horizons.

Indeed, when conducting BMA, supervisors rely on various sources, including banks' financial reporting; business plans; and internal reporting. BMA is conducted by examining banks' business environment and dialogues with internal and external stakeholders. In assessing banks' riskiness, supervisors should consider financial data and non-financial information disclosure (EU, 2014 Non-Financial Reporting Directive - NFRD) to detect risk drivers and crisis determinants not yet investigated in their current analysis models (EU, 2014).

Besides the relevance given to BMA, a growing number of supervisors expect banks to prudentially address the risks derived from climate change by adjusting the existing risk management frameworks and implementing ESG policies (BIS, 2019). More specifically, climate change affects the banking system's safety through physical and transition risks (Monasterolo, 2020). This adverse scenario has brought banking supervisors to ensure banks properly detect, manage, and disclose these risks (EBA, 2020a; EBA, 2021a). In this perspective, the

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European Central Bank (hereafter ECB) stimulate financial institutions to become more resilient to financial risk, climate, environmental and transition shocks, contributing to the safety and soundness of the banking sector and the overall financial system (ECB, 2020).

Besides the environmental (ENV) dimension, social (SOC) and governance (GOV) profiles can affect suitable economic development and mitigate the bank's riskiness profile. In the broader context of non-financial information, ESG policies have been the most relevant dimension of analysis, driven by growing shareholder and stakeholder pressure on the issue (Houston & Shan, 2022). As the European Banking Authority (hereafter EBA) has highlighted, greater attention to ESG factors can improve banks' reputation and mitigate the impact of ESG risks on financial assets held on the financial institutions' balance sheet. Consequently, regulatory forces - such as ECB and EBA - stress the adoption of BMA into the Supervisory Review and Evaluation Process (SREP) (EBA, 2014) and push financial intermediaries towards the inclusion of climate-related and environmental risks into the supervisory business model and internal governance analysis (EBA, 2021a). In the process of convergence towards a holistic assessment of banking risks, EBA (2021b) fosters the adoption of a unique ESG risk taxonomy to facilitate the integration of non-financial information into the banking regulatory and supervisory framework.

In the banking literature, many authors faced the BMs topic, addressing two main approaches. One of these is focused on the use of systematic quantitative methods, such as clustering analysis (Farnè & Vouldis, 2021a, 2021b; Ayadi, Bongini, Casu, & Cucinelli, 2021; Lagasio & Quaranta, 2022) to identify subgroups of banks characterized by a similar balance sheet composition. The other one is focused on the analysis of the relationship between BMs and banks performance/efficiency (Badunenko, Kumbhakar, & Lozano-Vivas, 2021; Mergaerts & Vander Vennet, 2016), bank risk (Altunbas, Manganelli, & Marques-Ibanez, 2011; Kohler, 2015) or capital endowment (Wheelock & Wilson, 2000). Besides this strand of studies, there has been growing academic attention on sustainable and ESG practices with empirical applications in non-financial firms (Chen & Xie, 2022; Palmieri, Ferilli, Stefanelli, Geretto, & Polato, 2023) and the banking industry (Chiaramonte, Dreassi, Girardone, & Piserà, 2022). In this literature body, recent studies by Neitzert and Petras (2019) and Gangi, Meles, D'Angelo, and Daniele (2019) link ESG to bank risk, finding a negative association and highlighting how ESG score and pillars act as significant drivers of bank risk-taking and value (di Tommaso & Thornton, 2020).

However, little is known about how banks' probability of default (PD) varies with their business model and ESG scores. This is particularly important given the relevance of business model choice (Roengpitya, Tarashev, Tsatsaronis, & Villegas, 2017) and ESG activities as a control mechanism to guide management decisions on banks' risk-taking (di Tommaso & Thornton, 2020). Indeed, there is a lack of studies regarding the effect of the interplay between BBMs and ESG pillars on banks' default risk.

In an attempt to bridge this gap, this paper detects the effect of ESG pillar scores on bank's probability of default (PD) according to their business models. We collect balance sheet data and ESG score information for a sample of 639 EU banks from 2013 to 2022 to examine the above objective. We define business models using clustering analysis on this sample. Then, as the first stage, using a random effects model, we estimate the effect of environmental (ENV), social (SOC) and governance (GOV) scores on bank's probability of default, taking into account the four categories of BMs identified. In the second stage, we corroborate the previous results by observing the effect on banks' PD arising from the interaction between *E*-S-G performances and BMs.

We contribute to the literature on the determinants of bank riskiness, with specific attention to banks' business models (Abdesslem, Chkir, & Dabbou, 2022; Altunbas, Manganelli, & Marques-ibanez, 2017; Wang, chiu, & Peña, 2017) and ESG practices (Bolton, 2013; Neitzert & Petras, 2019; Nguyen, Diaz-Rainey, Kuruppuarachchi, McCarten, & Tan, 2023).

Our findings suggest that the ESG profile and bank's business model matter for default probability mitigation. In particular, we offer a short- versus long-term perspective regarding the magnitude of bank's riskiness reduction, showing that in some specific BBMs, the default risk mitigation is remarkable in the long-term horizon.

We also contribute to the debate on ESG practices in banking by providing evidence that high ENV and GOV pillar scores act as a mitigator of bank's PD and are more effective in reducing risk-taking when banks have wholesale and retail BM, respectively. In this regard, the paper helps to address supervisory and regulatory concerns about whether and to what extent bank's riskiness is affected by its business model and ESG performance. We shed light on the existence of an optimal combination between the business model and ESG pillar enhancements that can decrease bank riskiness. Therefore, our paper offers practical implications for banking supervisory authorities and practitioners, encouraging to adopt a diversified ESG investment strategy according to bank-specific BM.

The remainder of the study is organized as follows. Section 2 proposes research hypotheses based on existing literature. Section 3 presents the model, main variables, and data sources. Section 4 discusses the empirical results and performs the robustness test. Section 5 highlights the implications and conclusions of the study.

2. Literature review and research question

2.1. Business models analysis and bank's riskiness

Business Model Analysis (BMA) has received growing attention from policymakers, regulators, and scholars (Farnè & Vouldis, 2021a, 2021b; ECB, 2018; EBA, 2018). This method goes beyond the traditional classification of banks based on their ownership structure (i.e., commercial, savings, and cooperatives) and has been included in the annual SREP in Europe, also becoming a top supervisory priority (Badunenko et al., 2021).

In the banking literature, the BM has been recognised as a crucial management tool that translates into several balance sheet and income statement ratios (Ayadi et al., 2021). Several studies have focused on the relationship between specific BMs characteristics and bank risk (e.g., Altunbas et al., 2011). In particular, prior to the financial crisis, scholars have focused on the interaction between risk and different key bank factors, such as capital (Wheelock & Wilson, 2000), funding sources (Demirgüc-Kunt & Huizinga, 2010), or operating efficiency (Kwan & Eisenbeis, 1997). Differently, after the financial demise, more attention has been paid on the investigations of determinants that affect banks performance, also using market information (Beltratti & Stultz, 2011; Ayadi et al., 2021; Badunenko et al., 2021). This study focuses exclusively on bank risk and the influence of BBM on the financial intermediaries' default risk.

As literature has highlighted (Altunbas, Gambacorta, & Marques-Ibanez, 2010; Haq & Heaney, 2012), bank risk is a complex and multi-faceted phenomenon; thus, in this study, we focused on the probability of default (PD) as a proxy of bank risk. Following authors such as Amel and Rhoades (1988); Farnè & Vouldis, 2021a, 2021b; and Ayadi et al. (2021), we implement clustering techniques, based on the bank financial statements, to classify our banking sample. According to previous findings (Amel & Rhoades, 1988), the identified bank groups share similar balance sheet compositions and are categorized according to the institution's focus on either retail or investment activities.

In this literature body, Farnè & Vouldis, 2021a, 2021b conducted a cluster analysis, identifying four distinct BBMs, and provided evidence that these sets of banks differ in terms of performance and risk indicators. While Ayadi et al. (2021) found that banks with higher risk and lower profitability are more likely to change their business model. This "migration" effect positively impacts bank performance, increasing both profitability and stability and enhancing cost efficiency.

2.2. ESG practices and banks' riskiness

In the broad literature stream that has analysed the positive impact of environmental, social, and governance (ESG) practices on financial performance (Palmieri et al., 2023; Trinh, Cao, Li, & Elnahass, 2023; Wong, Batten, Mohamed-Arshad, Nordin, & Adzis, 2021), a more recently sub-stream of literature has focused on the link between ESG practices and bank risk, showing - in more cases - a negative association (e.g., Bolton, 2013; Citterio & King, 2023; di Tommaso & Thornton, 2020; Gangi et al., 2019; Neitzert & Petras, 2019). This increasing attention on ESG factors in the risk assessment process arises from the actions taken by regulators and supervisors to encourage financial intermediaries to integrate climate and environmental risks into their BMA and internal governance analysis. As some authors have highlighted, ESG scores are strongly associated with a reduction in banks' risk-taking. According to di Tommaso and Thornton (2020), high ESG scores are associated with a modest reduction in risk-taking for banks that are high or low risk-takers. At the same time, Citterio and King (2023) demonstrate how the inclusion of ESG dimensions strongly reduces the likelihood of misclassifying distressed banks as healthy, emphasizing the importance of embracing the ESG information in the model used to detect bank financial distress. Although the current literature has investigated the link between ESG and bank risk, only a few studies have analysed the separate effects of environmental (ENV), social (SOC), and governance (GOV) scores on bank riskiness profile. In this field, Chiaramonte et al. (2022) found that ESG sub-pillars reduce bank fragility during periods of financial distress. Gangi et al. (2019), focusing on the CSR dimension, found that banks that are more sensitive to ESG issues exhibit less risk. In general, the current literature suggests a negative relationship between banks' ESG performance and riskiness profile. Therefore, banks with strong ESG performance may be perceived as having better governance policies and efficient risk management systems. These best practices lead to lower risk levels and better financial performance.

In order to enlarge the knowledge explored in the literature mentioned above, it is crucial to inquire the relationship between BBM and ESG pillars, adding a new element of knowledge in this field of research. The study aims to jointly consider BBM and ESG pillars performance in assessing their impact on banks' default risk. Hence, in line with EBA expectations and current academic interest in the topic, we outline the following research question (RQ):

RQ1: *Do ESG pillars mitigate banks' default probability differently depending on their business model?*

3. Research design: sample and methodology

3.1. Data and sampling

We collect financial data on individual European banks from the Refinitiv Datastream and Bloomberg to answer our research question. To stand a chance of inclusion in the analysis, the bank must have the data necessary to perform clustering analysis for 2013 to 2022. Our final sample comprised 639 European banks with 6390 bank-year observations. The period captures key regulatory changes, such as implementing the Basel III framework in the EU to fortify capital adequacy and liquidity standards. Concurrently, the institution of the Single Supervisory Mechanism (SSM) and Single Resolution Mechanism (SRM) has promoted a more cohesive and standardized methodology for banking oversight and resolution procedures. In a related strain, the modifications to the Markets in Financial Instruments Directive (MiFID II) have profoundly influenced operational methodologies and client data management. Finally, following the Paris Agreement on Climate, the financial industry has developed a growing interest in ESG and climate-change-related issues.

3.2. Methodology

Our methodology consists of two main steps. In the first step, we implement a clustering analysis (European Central Bank ECB, 2016; Ayadi et al., 2021) to classify the banks of our sample according to their BMs. We employ a random effect model to answer our research question in the second step. Moreover, to better control for the issue of endogeneity, we run the instrumental variables (IV) two-stage least squares (2SLS) regression estimation, as a methodology widely used in banking studies (Cubillas & González, 2014; Khan, Scheule, & Wu, 2017).

3.2.1. Business model analysis: variables and clustering technique

We found in the current literature the most representative variables able to build a valuable dataset for BBMs' cluster analysis (Appendix 1). Assuming that banks choose their BM, the variables adopted to define the BMs are based on the balance sheet items that banks have complete control over and can manage. Specifically, following the European Central Bank ECB (2016) and Ayadi et al. (2021) approach, we consider several balance sheet variables: (i) *deposits on the total asset,* to assess the ability of the bank to attract short-term funding sources from customers; (ii) *interbank assets to the total asset*, in order to evaluate to what extent the bank uses the interbank market to find sources of financing; (iii) *loans to total asset,* to express the importance of credit granting activities within the BM; (iv) *derivatives to total assets,* to explicit the usage of derivatives instruments in order to carry out speculative or hedging transactions; and (v) *trading assets to total asset,* that summarizes the amount of invested assets.

As our starting point for the identification of BBMs by cluster analysis, we execute *Ward's minimum variance method* (Ward & Joe, 1963), which is an agglomerative hierarchical clustering algorithm that uses distance function minimization to create clusters (Murtagh & Legendre, 2014). All bank-year observations are grouped together, and Ward's algorithm is applied for each year of observation. In this way, it is possible to determine banks' business model changes over time for each credit institution. Each bank in our sample has been grouped in a unique cluster based on the values presented in each clustering variable. The same bank could be grouped in different BM clusters during different time frames if they experience transitory shocks on the clustering variables.

In line with Rousseeuw (1987), we perform three distinct methods (i.e., elbow, silhouette, and gap statistic) to identify the ideal number of clusters (k*). As shown in Fig. 1, our cluster analysis results document the presence of four BMs:

(a) *Diversified Assets banks (BM1)* are identified by a more diversified assets composition towards non-traditional banking activities such as stocks, bonds, liquid assets, and financial derivatives, compared to the retail model. This cluster of banks does not present an excessive prevalence of one asset over the others. It represents the baseline business model in our regression with dummy interactions.

(b) *Investment* banks (*BM2*) are characterized by an extensive portfolio of securities, the use of derivative instruments, and an income statement focused mainly on commission margins. This locution is chosen to incorporate the investment activities carried out by banks on behalf of third parties and their own account;

(c) *Wholesale banks (BM3)* are known as intermediaries wholesale oriented and predominantly active in the interbank markets that are a primary source of financing and they mainly engage in intermediation with other banks, heavily relying on borrowing and lending among themselves.

(d) *Retail banks (BM4)* are qualified by the prevalence of loans to customers within the composition of their activities and are mainly financed by the collection of deposits. These banks are more stakeholder-oriented and tend to positively impact the real

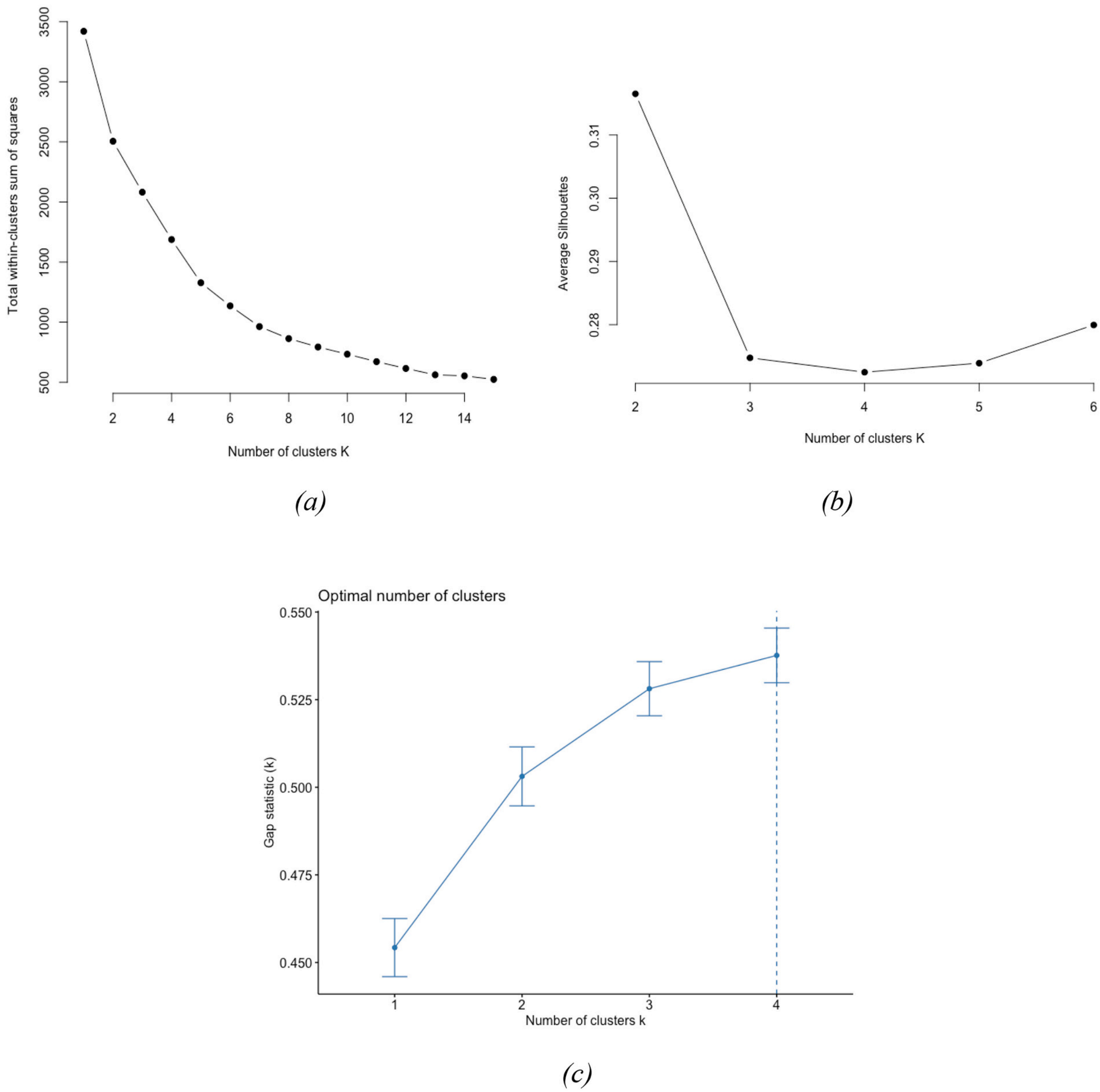

Fig. 1. Elbow method (a), Silhouette method (b), Gap statistic method (c).
Graphical representation of the techniques implemented to identify the ideal number of clusters.

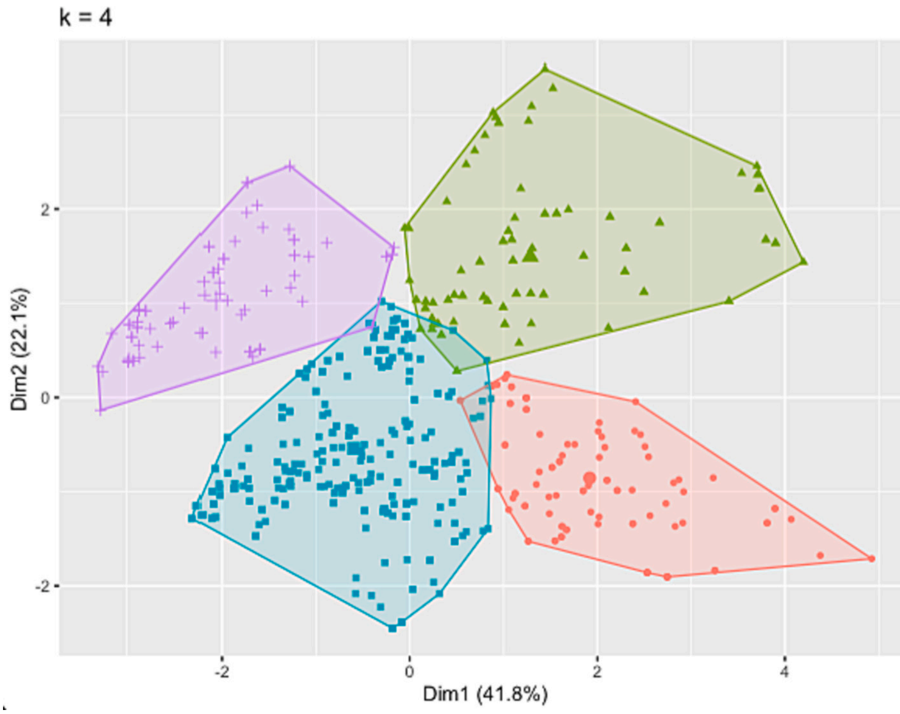

Fig. 2. Clustering graphical representation.
k = 4 represents the division in 4 clusters; Dim1 and Dim2 refer to the first and second principal components or dimensions, respectively, in a PCA analysis.

economy while preserving suitable performance and reducing risk for the entire financial system (Appendix 2).

The clustering algorithm results are coded as an integer value from one to four, following the number of BMs described above. Consequently, we update the dataset and create a set of four dummies to attribute one of the BM identified to each bank from the clustering algorithm. The final results of the clustering technique are provided in Fig. 2.

3.2.2. *Econometric model*

In the second stage of our analysis, we perform an econometric model to answer our research question. The Hausman test reveals that a random effect model is preferable to ensure the robustness of our findings. We use the following equation:

$$PD_{kit} = \alpha_{it} + \sum_{i=1}^{4}\sum_{j=1}^{3}\beta_{ij}{*}ESG_{pillar_{it}}{*}BM_{jt} + \sum_{k=1}^{4}\lambda_k{*}Control_{kt} + \phi_1{*}Bank_{eff} + \phi_2{*}time_{eff} + \epsilon_i$$

Where the probability of default (PD) is a proxy of the riskiness of bank *i* at time *t*. In this study, we employ a PD built by Bloomberg on Merton's distance to default measures. Specifically, we collect the PD data from Blomberg the PD from one to five years (recalling respectively as PD1, PD2 up to PD5).

As variables of interest, we use two main categories of variables. The first one is the disaggregate ESG scores on the three sub-pillar values; where [ENV] represents the environmental score (resulting from the weighted average of three constituents: Reso*urce Use; Emissions and Innovation*)), [SOC] explains the social score (based on four indicators: *Workforce; Human rights; Community and Product Responsibility*); and [GOV] denotes the governance score (based on three constituents: *Management; Shareholders and CSR Strategy*). The second one is the BMs dummy variable. We use dummy variables to express if banks belong to a BM rather than another. We omit the dummy representative of the fourth BM because any contribution in this sense can be observed in the constant. Moreover, consistently with studies examining the relationship between ESG score and riskiness (Di Tommaso & Thornton, 2020), we control for additional variables that may affect banks' riskiness, both bank-specific, namely banks' total capital ratio (TCR) to express the capital endowment necessary for the bank to cope with any losses due to risk-taking, and the natural logarithm of risk-weighted assets (RWA) to highlight risk-taking policies and capital absorption, and macroeconomic controls such as the natural logarithm of gross domestic product (GDP) and inflation rate (INF) (Beutler, Gubler, Hauri, & Kaufmann, 2021).

Appendix 3 presents the results of correlations between the independent variables. Furtherly, the VIF procedure confirms that each variable's average variance inflation factor is less than a threshold of 10 (Wooldridge, 2016). Consequently, multicollinearity is not a problem in this study.

To strengthen the validity of our findings, we employed an instrumental variables (IV) two-stage least squares (2SLS) regression. We used market capitalization (MKT), leverage (LEV), and z-score (ZSC), as instrumental variables, to address endogeneity concerns (Chiaramonte et al., 2022). To further address endogeneity concerns, we employ the Arellano coefficient methodology in combination with our 2SLS estimation, following Arellano and Bover (1995). This approach is validated by applying the Cragg-Donald and First Stage F tests, affirming our instrumental variable's strength while ensuring the absence of endogeneity issues.

Table 1
Baseline Results according to Banks' business model subgroups.

	Diversified	Investment	Wholesale	Retail	Diversified	Investment	Wholesale	Retail
			PD1				PD2	
Constant	−6.346	−1.618	23.080**	−2.946	−35.106***	−8.733	34.346***	−10.088
	(11.812)	(12.066)	(11.553)	(12.073)	(9.992)	(11.514)	(10.418)	(9.296)
ENV	0.0001	0.0002	0.001	0.001	−0.001	−0.0005	−0.002	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SOC	0.004**	0.007***	0.003*	0.007***	0.009***	0.012***	0.006***	0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GOV	0.001	−0.002***	0.002	0.002	0.001	−0.004***	0.004**	0.003*
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
TCR	0.0001	0.0001	−0.00004	−0.0002	0.002***	0.0001	−0.00004	0.0002
	(0.0002)	(0.0001)	(0.00003)	(0.0004)	(0.0002)	(0.0001)	(0.00003)	(0.0003)
log(RWA)	−0.124***	−0.159***	−0.200***	−0.187***	−0.108***	−0.238***	−0.232***	−0.241***
	(0.022)	(0.028)	(0.024)	(0.025)	(0.020)	(0.026)	(0.022)	(0.021)
GDP	0.284	0.153	−0.639*	0.201	1.224***	0.442	−0.983***	0.457
	(0.385)	(0.394)	(0.377)	(0.393)	(0.326)	(0.376)	(0.340)	(0.302)
INF	−0.025	−0.010	0.003	−0.010	−0.092*	−0.022	0.004	0.021
	(0.060)	(0.024)	(0.054)	(0.041)	(0.055)	(0.026)	(0.044)	(0.021)
Bank fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Time fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Observation	1959	1396	1757	1278	1959	1396	1757	1278
F Statistic	59.821***	56.879***	96.074***	118.702***	304.634***	164.867***	221.467***	555.746***
			PD3				PD4	
Constant	−53.266***	−13.871	31.402***	−28.100***	−65.226***	−17.391	27.498***	−47.187***
	(9.465)	(11.149)	(10.057)	(8.279)	(9.230)	(10.874)	(9.858)	(8.056)
ENV	−0.002	−0.001	−0.004**	−0.004**	−0.003**	−0.001	−0.006***	−0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
SOC	0.010***	0.013***	0.007***	0.023***	0.011***	0.013***	0.008***	0.025***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
GOV	0.002	−0.004***	0.005***	0.003**	0.002	−0.004***	0.005***	0.003**
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
TCR	0.003***	0.0001	−0.00002	0.001	0.004***	0.0001	−0.00000	0.001**
	(0.0002)	(0.0001)	(0.00003)	(0.0003)	(0.0002)	(0.0001)	(0.00003)	(0.0003)
log(RWA)	−0.036*	−0.210***	−0.160***	−0.195***	0.035*	−0.168***	−0.083***	−0.118***
	(0.019)	(0.025)	(0.021)	(0.019)	(0.018)	(0.025)	(0.021)	(0.019)
GDP	1.785***	0.603*	−0.917***	1.019***	2.143***	0.702**	−0.822**	1.606***
	(0.309)	(0.364)	(0.328)	(0.269)	(0.301)	(0.355)	(0.322)	(0.262)
INF	−0.123**	−0.029	−0.031	0.015	−0.140***	−0.033	−0.062**	0.002
	(0.052)	(0.027)	(0.036)	(0.017)	(0.049)	(0.027)	(0.031)	(0.017)
Bank fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Time fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Observation	1959	1396	1757	1278	1959	1396	1757	1278
F Statistic	529.664***	165.004***	204.072***	807.295***	731.490***	140.033**	* 186.396**	* 871.097***
			PD5					
Constant	−75.085***	−20.535*	27.114***	−61.428***				
	(9.137)	(10.730)	(9.766)	(7.965)				
ENV	−0.004***	−0.002	−0.008***	−0.006***				
	(0.001)	(0.002)	(0.002)	(0.002)				
SOC	0.012***	0.013***	0.009***	0.027***				
	(0.001)	(0.002)	(0.002)	(0.001)				
GOV	0.002	−0.005***	0.005***	0.003**				
	(0.001)	(0.001)	(0.002)	(0.001)				
TCR	0.004***	0.0001	0.00001	0.001***				
	(0.0002)	(0.0001)	(0.00003)	(0.0003)				
log(RWA)	0.082***	−0.149***	−0.040*	−0.076***				
	(0.018)	(0.024)	(0.021)	(0.019)				
GDP	2.446***	0.801**	−0.826***	2.052***				
	(0.298)	(0.350)	(0.319)	(0.259)				
INF	−0.156***	−0.037	−0.083***	−0.007				
	(0.047)	(0.028)	(0.028)	(0.017)				
Bank fixed effect	yes	yes	yes	yes				
Time fixed effect	yes	yes	yes	yes				
Observation	1959	1396	1757	1278				
F Statistic	950.574***	138.551***	213.823***	993.672***				

4. Empirical results

4.1. The results of BBMs subgroup analysis

Table 1 exhibits the results of the BMs subgroup analysis. Firstly, banks have been categorized according to their respective BM. As dependent variables, we have examined default probabilities over different time horizons, beginning with one year (PD1), and extending to five years (PD5).

The results show how, for the PD1, the intercept coefficients differ according to business models. The diversified, investment, and retail models have coefficients of −6.346, −1.618, and − 2.946, respectively, while the wholesale model has a statistically significant value of 23.080**. Over a 2-year horizon (PD2), the intercept for the diversified model significantly deviates to −35.106***, while the intercept for the wholesale model inverts to a significant 34.346***. By the fifth year (PD5), all business models demonstrate significant intercepts, with BM1 decreasing to −75.085*** and wholesale increasing to 27.114***.

Turning our focus to the environmental variable (ENV), its coefficients, while nominal across the PD1, adopt a negative trajectory from PD2 onwards. For example, at PD3, the ENV coefficients for wholesale and retail stand at a significant −0.004**. This trend intensifies by PD5, evidenced by coefficients of −0.008*** and − 0.006*** for wholesale and retail banks. The less noticeable trend observed in retail banks arises from the consumer-oriented model of these intermediaries.

Differently, retail banks, often characterized by their consumer-oriented nature, also display a comparable but somewhat less noticeable trend with a coefficient of −0.006*** by PD5. The retail banking space is influenced mainly by consumer sentiment and regulatory directives focused on consumer protection. As environmental awareness among consumers increases, their preferences and behaviours are evolving. This might entail a shift towards sustainable products or services and could influence their financial stability and creditworthiness in an environment-driven economy. Moreover, regulatory bodies aiming to protect individual consumers are pressing retail banks to embed environmental considerations into their lending practices. This regulatory push, combined with changing consumer behaviours, could be amplifying the sensitivity of retail banking to the ENV variable.

Retail banks are more influenced by consumer sentiment and regulatory requirements focused on consumer protection as consumers become more aware of environmental issues, their preferences and behaviour may evolve towards sustainable approaches, potentially resulting in a shift towards sustainable products or services. This could impact their financial stability and creditworthiness within an environmentally driven economy.

Furthermore, regulators, with the aim of safeguarding individual consumers, are applying pressure on retail banks to integrate environmental factors into their lending practices (such as the EBA's Loan Origination and Monitoring-LOM). This regulatory initiative and shifting consumer habits may increase retail banking's responsiveness to the ENV metric.

It is pivoting to the social factor (SOC), a persistent and robust positive correlation is discerned across all temporal default probabilities and business models. To clarify, the SOC coefficient for PD1 is presented as 0.004** for BM1, 0.007*** for investment, 0.003* for wholesale, and 0.007*** for retail. This consistency persists through PD5, showing coefficients ranging from 0.012*** in BM1 to a peak apex of 0.027*** in the retail model. This trend may be attributed to diversified BM-specific operational nuances or its exposure to particular market segments, where social factors significantly influence credit decisions or customer behaviour. The positive association between banks' SOC pillar scores and PD can be explained, in the first instance, as a consequence of overinvestment in social initiatives. From a financial perspective, if a bank channels resources towards more "social-oriented" loans without a robust risk assessment, it might see an uptick in non-performing assets. Concurrently, an undue emphasis on the social dimension could lead to potential neglect of fundamental financial and operational metrics, undermining the banks' financial resilience. Moreover, an elevated social score might sometimes be a compensatory mechanism in response to operational or ethical lapses elsewhere, thereby signalling institutional vulnerabilities that could increase the risk of default.

The investment banking model suggests a more robust short-term correlation with SOC. This may be attributed to investment banks' operations typically entailing substantial stakeholder engagements, mergers, acquisitions or capital market activities whereby social perceptions, reputation, and considerations can potentially exert an enlarged impact on investment decision-making and risk evaluation. Finally, the retail banking model highlights that social factors considerably affect retail banks. This increased sensitivity can be attributed to the direct engagement with individual customers, where social aspects like community relationships, customer attitude, and local societal norms can significantly influence banking decisions, customer faith, and loan-paying behaviours (REF).

Focusing on the governance variable (GOV), we observe a dichotomy of associations. In the short term, as PD1, the GOV coefficient for investment banks shows a negative correlation of −0.002***. By PD2, this negative association strengthens, reaching −0.004*** in the investment model. Conversely, wholesale and retail exhibit positive correlations of 0.004** and 0.003*, respectively. In the long term, the negative correlation of PD5 with investment remains at −0.005***, while wholesale and retail sectors maintain their positive trends, recording 0.005*** and 0.003**, respectively. In the investment banking model context, the discernibly negative association with the GOV variable could be rooted in the complex, high-risk, high-reward nature of investment banking activities. Often, these activities entail intricate financial products, mergers and acquisitions, and capital market operations. The negative coefficient might suggest that more robust governance mechanisms, often with increased scrutiny and control layers, could potentially slow down decision-making processes or limit flexibility, which might be perceived as obstacles in high-stakes, fast-paced investment scenarios.

Nevertheless, our findings demonstrate that better governance practices, although they may create operational frictions in the bank's core business when correctly applied, lead to a reduction in the bank's default risk.

Conversely, we observe a positive association of the GOV variable with wholesale and retail banking models. More specifically, wholesale banking, which involves substantial funding operations with other financial institutions, relies on a strong reputation and trust. In this context, bolstered governance practices may be perceived as a sign of reliability and due diligence, instilling greater confidence among clients and counterparts.

Similarly, in the retail banking model, where interactions are primarily with individual customers, the factor of trust plays a crucial role. Retail banking customers, who often lack detailed knowledge of financial products, deeply trust the bank's reputation and integrity. In this regard, robust governance mechanisms can enhance the bank's image, foster trust, and ensure customers feel their investments and interests are safe.

Finally, looking at control variables, we find that TCR reveals minimal changes across BBMs in the short period; however, the effect becomes significant and positive in the long time horizon (e.g., PD5) for the diversified banking model. This could infer that capital adequacy becomes a more significant determinant of performance or risk for diversified banks as time progresses. The natural logarithm of Risk-Weighted Assets (log(RWA)) presents consistent negative associations across all business models and temporal default probabilities. This denotes the inverse relationship between risk exposure and the metric under consideration, whether performance, risk, or any other dependent variable Gross Domestic Product (GDP) offers a mixed bag of coefficients, with diversified banking showing an increasingly positive and significant relationship by PD5. This might hint at the broader economic strength's role in influencing banks' riskiness. Inflation (INF) consistently exhibits small negative coefficients for most business models, particularly the diversified and investment sectors by PD5. It indicates the negative influence inflationary pressures might exert on these banking models over extended periods.

This could infer that as time progresses, capital adequacy becomes a more significant determinant of risk for diversified banks. The natural logarithm of Risk-Weighted Assets (log(RWA)) consistently shows negative correlations across all business models and temporal default probabilities. Gross Domestic Product (GDP) presents a mix of coefficients, with diversified banking demonstrating an ever-increasing positive and significant correlation by PD5. This implies that the broader economic stability could fundamentally affect banks' riskiness. Inflation (INF) consistently shows small negative coefficients for most

Table 2
Interaction results between bank business model and ESG sub-pillar scores.

	PD1	PD2	PD3	PD4	PD5
Constant	16.257***	5.801	−7.832	−19.387*	−27.256**
	(3.564)	(7.163)	(9.080)	(10.332)	(11.542)
ENV	0.003***	0.003	0.002	0.001	0.001
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)
SOC	0.005***	0.010***	0.012***	0.013***	0.014***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
GOV	−0.001	0.0001	0.001	0.001	0.002
	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)
TCR	−0.0001**	−0.00003	0.00001	0.00004	0.0001
	(0.00002)	(0.00005)	(0.0001)	(0.0001)	(0.0001)
log(RWA)	−0.214***	−0.281***	−0.225***	−0.156***	−0.121***
	(0.008)	(0.016)	(0.021)	(0.023)	(0.026)
GDP	−0.409***	−0.030	0.388	0.734**	0.977***
	(0.116)	(0.233)	(0.295)	(0.336)	(0.375)
INF	0.001	−0.036**	−0.060***	−0.076***	−0.089***
	(0.008)	(0.015)	(0.019)	(0.022)	(0.025)
Investment	0.191*	0.614***	0.830***	0.932***	1.010***
	(0.099)	(0.198)	(0.252)	(0.286)	(0.320)
Wholesale	−0.175*	−0.221	−0.153	−0.082	−0.049
	(0.104)	(0.210)	(0.266)	(0.302)	(0.338)
Retail	−0.120	−0.220	−0.236	−0.228	−0.234
	(0.105)	(0.211)	(0.267)	(0.304)	(0.340)
ENV * Investment	−0.002	−0.004	−0.005	−0.005	−0.005
	(0.001)	(0.003)	(0.004)	(0.004)	(0.005)
ENV * Wholesale	−0.001	−0.002	−0.003	−0.003	−0.003
	(0.001)	(0.003)	(0.004)	(0.004)	(0.005)
ENV * Retail	−0.003**	−0.007**	−0.008**	−0.008*	−0.008
	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
SOC * Investment	0.001	0.0004	−0.001	−0.002	−0.003
	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
SOC * Wholesale	0.001	0.002	0.003	0.003	0.003
	(0.002)	(0.004)	(0.005)	(0.005)	(0.006)
SOC * Retail	0.003*	0.008**	0.010**	0.011**	0.011*
	(0.002)	(0.004)	(0.005)	(0.005)	(0.006)
GOV * Investment	−0.001	−0.004	−0.005	−0.005	−0.006
	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)
GOV * Wholesale	0.003	0.004	0.003	0.002	0.002
	(0.002)	(0.004)	(0.005)	(0.006)	(0.006)
GOV * Retail	0.003	0.003	0.002	0.002	0.001
	(0.002)	(0.004)	(0.005)	(0.006)	(0.006)
Bank fixed effect	yes	yes	yes	yes	yes
Time fixed effect	yes	yes	yes	yes	yes
Observations	6390	6390	6390	6390	6390
R2	0.156	0.103	0.066	0.046	0.039
Adjusted R2	0.154	0.100	0.063	0.043	0.036
F Statistic	62.108***	38.404***	23.658***	16.23***	13.465***

business models, especially the diversified and investment sectors by PD5. This suggests that inflationary pressures may have a negative impact on these banking models over extended periods.

4.2. The results of the interaction between the BBM and ESG pillars

This section provides the main findings arising from the interaction between the BBM and the bank's ESG pillars. The aim is to capture the joint effect of these two dimensions of analysis on bank's riskiness. Table 2 presents the results, considering any potential interaction between the business model and ESG pillars. We decided to multiply each BM for the individual ESG pillars to assess the risk mitigation effect produced by improvement in specific ESG scores, discriminating against banks' business models. For the constant expression of the diversified asset business model, PD1 exhibits a value of 16.257***. This constant indicates a decreasing trend has shifted to −27.256** by PD5. Each regressor will be interpreted as a shift from the diversified asset baseline level.

The ENV factor for PD1 is documented as 0.003***. However, when examining PD5, this coefficient decreases to 0.001. The SOC factor shows a rising trend over the years. It is recorded as 0.005*** for PD1, reaching its peak at 0.014*** by PD5. The GOV factor remains relatively stable, starting with a negligible value at PD1 and gradually increasing to 0.002 by PD5. The TCR coefficient starts with a value of −0.0001** for PD1. In the long-time horizon, this value becomes positive, remaining small in magnitude.

The logarithm of Risk-Weighted Assets (log(RWA)) consistently shows negative coefficients throughout all years. GDP reflects a shift from an initial coefficient of −0.409*** for PD1 to a positive 0.977*** by PD5. For PD1, the coefficient is −0.214*** and for PD5, it is −0.121***. The coefficient for PD1 of the Inflation (INF) predictor is negligible but is noted at −0.089*** by PD5. Investment exhibits a consistent positive correlation with default probabilities, represented by a 0.191* coefficient for PD1, increasing to 1.010*** for PD5. The Wholesale factor is observed to have a − 0.175* coefficient for PD1, with its impact decreasing by PD5. The retail coefficient remains negative without significant variation across all periods.

For banks that adopt an investment-focused BM, there is a clear and increasing relationship with the probability of default (concerning the baseline business model exhibited in the constant). At the one-year mark (PD1), the regression coefficient for these banks is 0.191*, which significantly rises to 1.010*** by the five-year horizon (PD5). This tendency suggests that banks relying heavily on an investment model may face increased default probabilities as we move further into the future. Banks following an investment-focused approach typically hold portfolios consisting of higher-risk assets, such as derivatives or

Table 3
2SLS Model and Arellano coefficient estimation.

	PD1	PD2	PD3	PD4	PD5
Constant	14.088***	2.339	−11.457	−23.042***	−31.129***
	(3.655)	(6.770)	(8.100)	(8.894)	(9.788)
ENV	0.004***	0.005***	0.004***	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
SOC	0.005***	0.010***	0.012***	0.013***	0.015***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
GOV	−0.001	0.001	0.001	0.002	0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
TCR	−0.00004	−0.00004	−0.00002	−0.00001	0.00000
	(0.00003)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
log(RWA)	−0.130***	−0.161***	−0.113***	−0.060	−0.030
	(0.013)	(0.031)	(0.041)	(0.047)	(0.051)
GDP	−0.400***	−0.010	0.411	0.758***	1.003***
	(0.120)	(0.220)	(0.261)	(0.286)	(0.313)
INF	−0.002	−0.040***	−0.064***	−0.080***	−0.093***
	(0.007)	(0.014)	(0.017)	(0.018)	(0.020)
Investment	0.251	0.701*	0.911**	1.003**	1.078**
	(0.206)	(0.384)	(0.419)	(0.413)	(0.425)
Wholesale	−0.152*	−0.189	−0.123	−0.057	−0.026
	(0.086)	(0.124)	(0.130)	(0.132)	(0.141)
Retail	−0.110	−0.204	−0.220	−0.213	−0.219
	(0.099)	(0.149)	(0.157)	(0.159)	(0.169)
predicted_PD	0.671***	0.678***	0.722***	0.785***	0.836***
	(0.067)	(0.118)	(0.178)	(0.249)	(0.302)
ENV * Investment	−0.001	−0.003**	−0.004**	−0.004**	−0.004**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
ENV * Wholesale	−0.0003	−0.001	−0.002	−0.002	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
ENV * Retail	−0.002**	−0.005***	−0.006***	−0.007***	−0.007***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
SOC * Investment	0.00001	−0.001	−0.002	−0.003	−0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
SOC * Wholesale	0.0003	0.001	0.002	0.002	0.002
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
SOC * Retail	0.002	0.007**	0.009***	0.009***	0.010**
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
GOV * Investment	−0.001	−0.004	−0.005	−0.005	−0.006
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
GOV * Wholesale	0.003	0.004	0.003	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
GOV * Retail	0.002	0.003	0.002	0.001	0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Bank fixed effect	yes	yes	yes	yes	yes
Time fixed effect	yes	yes	yes	yes	yes
Observations	6391	6394	6397	6400	6403
F Statistic	166.863***	94.060***	54.435***	35.468***	28.605***

securities. The drive to achieve greater short-term returns may lead to increased risk. As the horizon lengthens, the inherent volatility and exposure to systemic shocks of such assets can cumulatively lead to an increased probability of default compared to diversified asset BM.

Banks grounded in a wholesale BM show different empirical evidence. The relationship between their business model and default probabilities starts with a coefficient of −0.175* for PD1 and decreases to −0.049 by PD5. This suggests that while there might be immediate concerns for default with the wholesale model, its impact lessens over a longer timeframe (concerning the baseline business model exhibited in the constant). Similarly, retail banks exhibit a negative relationship with default probabilities across the years, with coefficients hovering from −0.120 for PD1 to about −0.234 by PD5. On the other hand, retail BM, characterized by numerous small transactions with individuals, exhibit steadier default probabilities, primarily due to diversified risks. The steady negative relationship could be attributed to the bank's proficient risk management and screening processes over the retail customers.

The interaction results provide deeper insights into the compounded effects of external factors, like the banks' ESG practices, with the business models adopted by the intermediaries. For instance, when ENV considerations are factored in the investment BM, we observe coefficients ranging from −0.002 at PD1, stabilizing around −0.005 by PD5. This suggests that ENV improvement for an investment bank produces an increment of default risks with respect to diversified assets. The interactions between ENV and wholesale and retail BMs have negative effects as well, suggesting that environmental factors in interaction with these business models may have a dampening effect on default probabilities. The increasing emphasis on sustainability and green financing by the EBA (2023) means banks that do not adhere to environmental compliance, especially those in the investment segment, are more vulnerable to reputational and financial risks (Galletta, Goodell, Mazzù, & Paltrinieri, 2023). This could lead to an increase in default probabilities. On the contrary, retail and wholesale banks, which are more oriented to establish direct interactions with consumers and businesses, might engage in more sustainable practices, improving ENV factors as a lever for risk mitigation compared to diversified asset BM.

Contrarily, the interactions between the SOC pillar and the different BBMs present nuanced patterns. The interaction between the investment model and the SOC pillar shows a negligible positive coefficient at PD1 but becomes negative at the 5-year mark. However, for banks with either wholesale or retail models, there is a mild upward trend in the interaction with SOC, particularly for the retail-focused banks, which start with a coefficient of 0.003* at PD1 and reach 0.011* by PD5. Social considerations shall represent a bank's relationship with its community, employees, and other stakeholders. An investment bank might gain from positive social engagements in the initial phases. However, in the long

Table 4
Cragg-Donald and First-stage F-test.

Test	PD1	PD2	PD3	PD4	PD5
Cragg-Donald	0.003368434	0.0003192043	0.0003158552	0.000243401	0.000312964
First-stage F-test	230.3983	116.2161	56.6902	29.13515	19.34758
P-value	4.702131e-185	7.929454e-96	4.540069e-47	4.862098e-24	7.754784e-16

term, community expectations versus the bank's pursuit of high returns might clash, leading to increased default risks.

Conversely, retail and wholesale models that are more community and customer-focused could benefit from positive social engagement, resulting in lower default probabilities. Governance (GOV) considerations, when combined with the investment business model, predominantly convey a negative trajectory, starting from −0.001 at PD1 and deepening to −0.006 at PD5. However, the relationship remains marginally positive when GOV considerations are intertwined with the wholesale model. In retail, the governance interaction is consistently minimal but positive. Governance norms play a key role in shaping banks' decision-making processes. Given their aggressive risk-taking stance, investment-oriented banks may experience escalating default risks if not matched by robust governance practices. Conversely, the more structured and customer-focused wholesale and retail models may already incorporate sound governance practices, leading to either minimal or marginally positive interactions with default probabilities.

4.3. Robustness check

To strengthen the validity of our findings, we run a set of further analyses and robustness checks. Firstly, addressing the potentiality endogeneity concerns, in Table 3, we adopted the two-stage least squares (2SLS) regression, using a set of instrumental variables. The instrumental variables, founded in previous studies (i.e., Chiaramonte et al., 2022), include total capital ratio (TCR), market capitalization (MKT), leverage (LEV), and z-score (ZSC), were selected strategically to identify exogenous changes, thus allowing a more refined understanding of the causal dynamics between our explanatory and response variables.

To strengthen our findings, we also run the model integrating the Arellano coefficient analysis (Arellano & Bover, 1995) to counteract any potential model distortions.

The 2SLS evaluation followed the Cragg-Donald application, which confirmed our approach by producing non-significant results, as shown in Table 4. This implies the appropriateness of our choice of instruments and ensures that their effectiveness has not been compromised. Such evidence has increased the robustness and reliability of our conclusions.

5. Conclusion, limits, and implications

In this study, we provide empirical evidence concerning the banks' business models capabilities to differentiate their risk mitigation effect through investment in individual ESG pillars.

Our findings show that regarding the environmental dimension, wholesale banks display a negative association between environmental (ENV) score improvement and default probability. Regulatory responses (EU, 2020) to global environmental challenges further amplify the potential default risks for banking institutions. Although, to a lesser extent, retail banks are also negatively associated with environmental issues. This differentiation arises due to the inherent customer-focused nature of retail banking (Liu & Wan, 2023). As the public's environmental consciousness increases and regulatory frameworks develop with a concentration on consumer protection, retail banks' risk profile undergoes slight transformations.

Regarding the social dimension (SOC), investment banks exhibit a strong initial positive relationship, which transitions into a negative one over a longer time horizon. The nature of investment banking activities, characterized by extensive stakeholder interactions and often tied to complex financial ventures, makes them particularly sensitive to social considerations. This susceptibility affects their risk assessments, influenced by social perceptions and stakeholder reputation. Additionally, retail banking, inherently rooted in direct interactions with individual consumers, emerges as exceptionally responsive to social factors. The intricate weave of societal norms, community sentiments, and individual consumer preferences plays a pivotal role in shaping the default risk profile for these banks.

Lastly, investment banks reveal a consistent negative association concerning the governance (GOV) pillar score. The multifaceted and often high-risk activities linked with investment banking may regard strict governance structures as potential constraints, which is reflected in their risk profile. In contrast, wholesale and retail BMs are positively associated with the GOV score. For wholesale banks, which are characterized by extensive transactions and trust-based operations, enhanced governance practices serve as a marker of reliability. Simultaneously, the fundamental aspects of retail banking, closely connected to individual consumers, emphasise the importance of robust governance in decision-making processes and building trust. Our paper contributes actively to the regulatory debate regarding climate and environmental risks in the banking sector (Nguyen et al., 2023). Through the lens of supervisory authorities, the present work, in line with the "ECB expectation n. 7", provides a novel empirical approach to incorporate ESG dimensions as an additional risk driver into banks' risk management framework (ECB, 2020b).

Additionally, in line with the EBA's expectations, the study's findings suggest that bank management should embrace ESG practices to secure the sustainability and resilience of their business model from a forward-looking perspective (EBA, 2021b). Furthermore, we support the need for legislators and academics to promote and implement education and disclosure activities to increase the knowledge and opportunities of environmental, social and governance risks. These interventions enhance risk management processes and guarantee more conscious investment decisions. Therefore, our research provides new empirical evidence that supports the effectiveness of the adoption of BBMs, also focused on ESG dimensions in the European banking industry.

Regarding financial stability improvement, policymakers and supervisory authorities should adopt a holistic approach in assessing banks' default probability, implementing a comprehensive business model analysis (BMA) for small-medium and larger financial institutions. BIS (2022) emphasises that the analysis of banks' business models (BMA) is a crucial component of the supervisory framework. The early-stage detection of banks' BMs vulnerability prevents bank failures and guarantees the safety and soundness of the financial system. Additionally, our findings support the need for greater attention to non-financial information disclosure (e.g., ESG pillars information), which, supported by the consolidated BMA, can enhance the bank's PD estimation. In this perspective, policymakers and regulatory authorities are encouraged to incorporate ESG performance into banks' risk assessment procedures. We are aware of the limits of our paper that should be addressed in future research. Firstly, from a methodological standpoint, the BMA carried out with cluster analysis is particularly sensitive to variations in clustering variables. Secondly, the present study only analyses the direct effect of each ESG pillars in banking institutions, missing the indirect effects (e.g., improvement in the environmental profile of the credit portfolio), which is difficult to monitor.

Future scholars could investigate how second-level ESG sub-indicators impact the banks' default probability. Furthermore, it could be analysed whether the risk-mitigation effect in the banking sector has regional and territorial differences. Besides the relevance of non-financial disclosure in this paper, we encourage scholars to deeply understand how a lack of disclosure could lead to market failures and distortions.

Data availability

No

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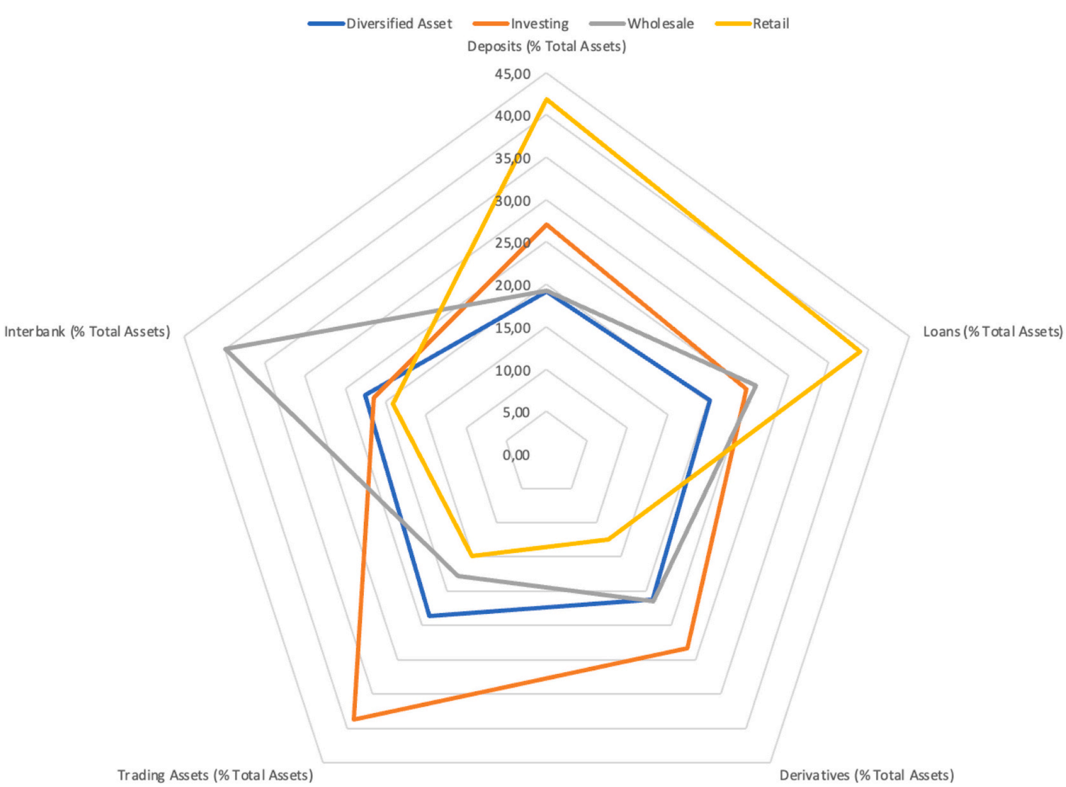
Appendix A. Clustering variables in literature

Reference	Loans (% Total Assets)	Interbank assets (% Total Assets)	Trading (% Total Assets)	Deposits (% Total Assets)	Derivatives (% Total Assets)	Interest Margin (% Revenues)
Amel and Rhoades (1988)						✓
Ayadi et al. (2016)	✓	✓	✓	✓	✓	
Roengpitya et al. (2017)	✓	✓	✓	✓		✓
Ayadi (2019)	✓		✓	✓	✓	
De Meo et al. (2016)	✓	✓	✓	✓	✓	✓
European Central Bank ECB (2016)	✓		✓			✓
Mergaerts and Vander Vennet (2016)				✓		✓
Ayadi et al. (2023)	✓		✓	✓	✓	

Appendix B. Bank business models after clustering



Appendix C. Correlation matrix

Variables	DEP_TA	LOAN_TA	DER_TA	TRADE_TA	INT_TA	RWA_TA	ESG	ENV	SOC	GOV	PD1	PD2	PD3	PD4	PD5	BM	GDP	INF	LMKT	TCR	LEV	ZSC
DEP_TA	1.00	−0.09	0.04	0.14	0.46	0.20	−0.02	−0.36	−0.01	−0.01	0.50	0.36	0.25	0.18	0.15	0.10	0.11	0.04	−0.54	0.02	−0.02	−0.02
LOAN_TA	−0.09	1.00	0.00	0.27	−0.03	0.12	0.00	0.13	0.01	0.00	0.13	0.14	0.12	0.11	0.10	0.18	−0.11	−0.05	0.03	−0.03	−0.02	0.02
DER_TA	0.04	0.00	1.00	0.03	0.04	0.28	−0.03	0.11	−0.05	−0.03	0.05	0.06	0.06	0.06	0.06	0.02	−0.07	−0.05	0.10	−0.02	−0.30	0.00
TRADE_TA	0.14	0.27	0.03	1.00	0.08	0.27	0.00	−0.08	0.01	0.01	0.17	0.25	0.26	0.25	0.24	0.04	0.06	−0.03	−0.15	0.01	−0.05	0.04
INT_TA	0.46	−0.03	0.04	0.08	1.00	0.12	−0.01	−0.12	−0.01	−0.01	0.42	0.28	0.19	0.13	0.10	0.03	0.00	−0.01	−0.25	0.03	−0.03	−0.01
RWA_TA	0.20	0.12	0.28	0.27	0.12	1.00	−0.01	−0.20	−0.01	−0.01	0.27	0.35	0.35	0.33	0.33	0.05	0.11	−0.01	−0.05	−0.04	−0.18	0.02
ESG	−0.02	0.00	−0.03	0.00	−0.01	−0.01	1.00	0.07	0.98	1.00	0.03	0.02	0.02	0.02	0.03	−0.01	−0.02	0.02	−0.01	0.00	0.01	0.00
ENV	−0.36	0.13	0.11	−0.08	−0.12	−0.20	0.07	1.00	0.08	0.04	−0.15	−0.12	−0.09	−0.06	−0.05	−0.03	−0.40	−0.13	0.52	−0.02	−0.02	0.03
SOC	−0.01	0.01	−0.05	0.01	−0.01	−0.01	0.98	0.08	1.00	0.97	0.06	0.05	0.05	0.05	0.05	−0.01	−0.07	0.01	−0.01	0.00	0.02	−0.01
GOV	−0.01	0.00	−0.03	0.01	−0.01	−0.01	1.00	0.04	0.97	1.00	0.03	0.02	0.02	0.02	0.02	−0.01	0.00	0.03	−0.02	0.00	0.01	−0.01
PD1	0.50	0.13	0.05	0.17	0.42	0.27	0.03	−0.15	0.06	0.03	1.00	0.85	0.71	0.61	0.55	0.08	0.00	−0.03	−0.35	0.02	−0.05	−0.03
PD2	0.36	0.14	0.06	0.25	0.28	0.35	0.02	−0.12	0.05	0.02	0.85	1.00	0.97	0.93	0.91	0.07	0.00	−0.04	−0.25	0.02	−0.05	−0.02
PD3	0.25	0.12	0.06	0.26	0.19	0.35	0.02	−0.09	0.05	0.02	0.71	0.97	1.00	0.99	0.98	0.06	0.00	−0.04	−0.18	0.02	−0.05	−0.01
PD4	0.18	0.11	0.06	0.25	0.13	0.33	0.02	−0.06	0.05	0.02	0.61	0.93	0.99	1.00	1.00	0.05	−0.01	−0.04	−0.12	0.02	−0.04	0.00
PD5	0.15	0.10	0.06	0.24	0.10	0.33	0.03	−0.05	0.05	0.02	0.55	0.91	0.98	1.00	1.00	0.04	−0.01	−0.03	−0.10	0.02	−0.04	0.00
BM	0.10	0.18	0.02	0.04	0.03	0.05	−0.01	−0.03	−0.01	−0.01	0.08	0.07	0.06	0.05	0.04	1.00	0.01	0.03	−0.08	0.00	0.00	0.01
GDP	0.11	−0.11	−0.07	0.06	0.00	0.11	−0.02	−0.40	−0.07	0.00	0.00	0.00	0.00	−0.01	−0.01	0.01	1.00	0.61	−0.26	0.02	0.03	0.03
INF	0.04	−0.05	−0.05	−0.03	−0.01	−0.01	0.02	−0.13	0.01	0.03	−0.03	−0.04	−0.04	−0.04	−0.03	0.03	0.61	1.00	−0.08	0.02	0.01	0.05
LMKT	−0.54	0.03	0.10	−0.15	−0.25	−0.05	−0.01	0.52	−0.01	−0.02	−0.35	−0.25	−0.18	−0.12	−0.10	−0.08	−0.26	−0.08	1.00	−0.02	−0.04	0.00
TCR	0.02	−0.03	−0.02	0.01	0.03	−0.04	0.00	−0.02	0.00	0.00	0.02	0.02	0.02	0.02	0.02	0.00	0.02	0.02	−0.02	1.00	0.00	−0.02
LEV	−0.02	−0.02	−0.30	−0.05	−0.03	−0.18	0.01	−0.02	0.02	0.01	−0.05	−0.05	−0.05	−0.04	−0.04	0.00	0.03	0.01	−0.04	0.00	1.00	−0.01
ZSC	−0.02	0.02	0.00	0.04	−0.01	0.02	0.00	0.03	−0.01	−0.01	−0.03	−0.02	−0.01	0.00	0.00	0.01	0.03	0.05	0.00	−0.02	−0.01	1.00

We exhibit the correlation matrix of the variable of interest.

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