



# ESG activity and bank lending during financial crises<sup>☆</sup>

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## ABSTRACT

This paper explores how banks' environmental, social, and governance (ESG) activities affect their lending during financial crises. We use a sample of European listed banks with available ESG scores from 2002 to 2020 and consider the global financial crisis of 2007–2009 and the European sovereign debt crisis of 2010–2012. We estimate a two-step system GMM dynamic panel data model and also address potential endogeneity with instrumental variable (IV) and difference-in-difference (DiD) estimations. We find that lending falls to a lesser extent for banks with higher ESG scores during crisis times. Our findings are robust to using alternative ESG rating providers. An investigation of the different potential channels shows that, during crises, banks more engaged in ESG activities are less affected in terms of credit risk, asset risk, and profitability. They also face a lower reduction in market funding, allowing them to downsize to a lesser extent during crises, and their deposit rates do not increase as much as in less ESG-engaged banks. A deeper investigation reveals that our findings mainly hold for banks focused on traditional lending and deposit activities and are essentially driven by the environmental pillar component of ESG scores and the global financial crisis of 2007–2009.

## 1. Introduction

There has been a growing interest in corporate social responsibility (CSR) and environmental, social, and governance (ESG)<sup>1</sup> from researchers, practitioners, and regulators, especially after the 2007–2009 global financial crisis (GFC) and more recently in the wake of the COVID-19 pandemic. Firms increasingly face internal and external pressures to improve their non-financial performance, and they consider ways to mitigate the negative environmental and social impacts to address the emerging needs of society. There are many empirical studies on how ESG activities influence non-financial firm performance, and the findings are mixed. Some studies find that ESG activities boost firm performance by providing product differentiation and reducing systematic risk (Friede et al., 2015; Broadstock et al., 2020, among others). Others claim that ESG activities might generate inefficiently allocated capital, lead to opportunity costs, and that the relationship is neutral or

even negative (Devinney, 2009; Oikonomou et al., 2012; Santis et al., 2016; among others).

Despite a considerable body of literature on its influence on non-financial firms, whether and how ESG engagement impacts financial institutions, particularly banks, has been relatively less explored. Banks have been in the spotlight to be more responsible to their customers and make more sustainable lending decisions (Hasan et al., 2022; Houston and Shan, 2022). Some recent studies have focused on how banks' CSR activity impacts bank value (Azmi et al., 2021), bank efficiency (Belasri et al., 2020), and bank stability (Di Tommaso and Thornton, 2020; Chiaramonte et al., 2022), also providing conflicting findings. This mixed evidence points to a need to better understand the conditions under which ESG activity is likely to influence bank outcomes. In this paper, we explore how ESG activities affect banks' lending during financial crisis times.

Growing evidence supports the view that, during crisis times, non-

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<sup>1</sup> CSR and ESG are increasingly used interchangeably in the literature.

financial firms with better ESG engagement have lower downside risk, and they are more resilient in terms of market performance (Lins et al., 2017; Albuquerque et al., 2020; Broadstock et al., 2021). Albuquerque et al. (2019) develop a theoretical model where ESG investments help firms improve their product differentiation, leading to a more loyal customer base and a lower price elasticity of demand in response to aggregate shocks. Recent literature documents the stabilizing effects of sustainability considerations in times of crisis in different financial settings, such as equities (Ding et al., 2021; Capelle-Blancard and Desroziers, 2020), and mutual funds (Pástor and Vorsatz, 2020; Nofsinger and Varma, 2014). Specifically, stocks with higher corporate social responsibility activities and mutual funds with high sustainability ratings perform well during the COVID-19 pandemic (Ding et al., 2021; Pástor and Vorsatz, 2020), and socially responsible mutual funds outperform conventional funds during periods of market crises (Nofsinger and Varma, 2014). Very few studies specifically focus on how ESG activities impact bank behavior during turbulent times; Cornett et al. (2016) and Chiaramonte et al. (2022) are some exceptions. These studies document that banks with higher ESG engagement have better financial performance and stability during crises, such as the GFC. But, whether and how ESG activities affect individual bank lending during financial crises remains an open question. To the best of our knowledge, no studies explore this issue.

Understanding how ESG activity affects bank lending, especially in crisis times, is essential because banks are greatly linked to environmental degradation through their lending activities. Banks rely on substantial resources from society, as most of their funding originates from depositors. They play a crucial role in allocating funds by considering the needs and preferences of savers and investors into appropriate capital investments (Scholtens, 2006). With their role as financial intermediaries and credit providers, they contribute to the development of the economy (Levine, 2005; Scholtens, 2009). Financial crisis times are characterized by higher information asymmetries (Flannery et al., 2013). During such times, banks face an overall decrease in funding, and thus they prefer lending to borrowers with whom they have a longer lending relationship. Moreover, banks become more cautious about lending due to the potential increases in loan defaults, leading to an overall reduction in lending (Ivashina and Scharfstein, 2010; Lou and Yin, 2014). Such reductions in the credit supply in crisis times have severe implications on the real economy, propagating the overall decrease in investments or employment (Berger et al., 2020). Hence, whether banks' involvement in ESG activities could influence their behavior in terms of lending during crisis times is an important question. If bank lending is differently affected because of banks' engagement in ESG principles, the implications for the real economy could be very different.

There is growing evidence that banks address carbon risk within their lending decisions, incorporated through credit risk assessment criteria and the cost of debt (e.g., Jung et al., 2018; Herbohn et al., 2019). They offer lower loan rates to firms with better corporate social responsibility performance (Cheung et al., 2018). They are motivated to boost their corporate social responsibility reputation to attract more creditworthy borrowers (Wu and Shen, 2013; Herbohn et al., 2019). They offer savings accounts that support socially and environmentally responsible projects (Scholtens, 2009). Houston and Shan (2022) document that banks are concerned about the ESG performance of their potential borrowers due to financial and reputational motivations. Specifically, they find that banks with strong ESG performance are more likely to lend to borrowers with better ESG ratings and positively influence the borrower's future ESG performance. Consistent with this, recent research has documented an association between firms' sustainability performance and loan pricing (Hasan et al., 2017). Hasan et al. (2022) find that banks' commitment to better climate-related disclosures causes borrowing firms to reduce polluting behavior and improve their environmental ratings.

The theoretical literature on the potential relationship between ESG

and firm value is based on two main opposing views. The "over-investment view" states that managers tend to overinvest in ESG for their personal benefits arising from agency theory or to gain support from society, and these investments are accepted as a waste of resources (Cespa and Cestone, 2007; Barnea and Rubin, 2010). Meanwhile, the "stakeholder theory" asserts that ESG investments benefit all stakeholders. By lowering idiosyncratic risk, asymmetric information, and agency costs, such investments are expected to reduce the cost of capital (Godfrey, 2005; El Ghouli et al., 2011; El Ghouli and Karoui, 2017) and improve access to finance (Cheng et al., 2014). If, as argued by the literature, firms with better ESG engagement are less severely impacted during crisis times than less engaged firms (Lins et al., 2017; Albuquerque et al., 2020; Broadstock et al., 2021), we should expect banks to continue to fund such entities more easily at the detriment of other firms. If, as documented in the literature (Houston and Shan, 2022; Hasan et al., 2022), banks with higher ESG scores are already engaged with firms with stronger ESG engagement, then we would also expect ongoing bank-firm relationships to be less likely interrupted, and overall lending activities consequently less affected during turmoil.

Our empirical analysis uses a sample of 83 European commercial banks with annual ESG scores available<sup>2</sup> from 2002 to 2020. We investigate the influence of ESG activity on bank lending during financial crisis times, i.e., considering both the GFC in 2007–2009 and the sovereign debt crisis in 2010–2012. In our baseline estimations, to account for the dynamic nature of lending, we conduct two-step system GMM dynamic panel data estimation techniques. Empirical studies testing the impact of ESG on firm performance or other outcomes suffer from identification issues. Indeed, whether ESG activities are actually beneficial for firms or whether more profitable firms engage in such activities simply because they can afford them remains an open question (Albuquerque et al., 2020). We address this empirical challenge by conducting two-stage least squares (2SLS) estimations with instrumental variables. We also conduct a difference-in-differences (DiD) analysis built around the financial crises. We analyze whether, during the financial crises, the lending of banks for which an ESG rating is available differs from that of almost identical banks that are not rated. Specifically, we generate a matched sample of ESG-rated and non-ESG-rated banks and compare their lending before (2002–2006) and during the financial crises (2007–2012). Our findings reveal that while all banks in our sample decrease their lending during crisis times, banks with higher ESG scores are less affected. Such banks can still, to some extent, continue to lend, whereas banks that are less ESG-engaged experience more difficulties performing their intermediation function. Our findings are robust to a variety of robustness checks, such as using alternative ESG rating providers,<sup>3</sup> controlling for the Paris Agreement, using alternative definitions of financial crises, and using alternative estimation methodologies to account for endogeneity. Our findings further continue to hold after controlling for time-varying country-level factors such as differences in mandatory ESG disclosures, sovereign risk, country's stakeholder orientation, and investor protection.

To go deeper, we examine the channels through which ESG activity affects bank lending during times of crisis. Specifically, we explore the impact of ESG on bank risk, banks' pricing behavior, and the components of their balance sheets in crisis times. Banks that are perceived as less affected by rises in credit risk and overall asset risk are more likely to maintain their lending activities than their peers. The same would hold

<sup>2</sup> We use ESG-related data from Refinitiv ASSET 4, which is one of the most comprehensive databases that contain more than 450 different historically available ESG metrics and is widely used in the literature (Albuquerque et al., 2020; Chiaramonte et al., 2022; among others).

<sup>3</sup> Since it is argued in the literature that ESG ratings may vary across different data providers with a low correlation (Berg et al., 2022), we also consider bank-level ESG ratings from two other data providers: FitchConnect and MarketPsych ESG Analytics.

for institutions suffering from a lower fall in profitability during turmoil or whose depositors are less likely to run or require higher interest rates. The structure of bank funding during uncertain times also has an important effect on bank lending (Ritz and Walther, 2015). Banks that are more likely to attract depositors who withdraw their holdings from jeopardized banks will also be able to lend more (Cornett et al., 2011). During crisis times, there is a dry-up in the wholesale funding market, and banks face market funding liquidity shocks, which are directly propagated into bank lending (Brei et al., 2013). The market would be more confident to lend to banks that are perceived as safer and such banks would have more funding sources to continue their lending activities.

We document that while crisis times negatively affect credit risk and, more generally, asset risk for all banks, banks with stronger ESG engagement are less impacted, possibly explaining that lending can continue to take place more easily during stressful periods. We also show that banks with higher ESG scores face a relatively lower decrease in their profitability and that the depositors of these banks request a lower increase in deposit rates in crisis times. Such banks are also the ones that suffer less from a fall in market funding and that downsize their balance sheet to a lesser extent during crises.

In further analyses, we go deeper and investigate the influence of banks' business models on the moderating impact of ESG on the decrease in lending during crisis times. We find that our results mainly originate from banks focused on traditional deposit and lending activities and that are less diversified into non-interest activities. Such banks are those that are the least affected in terms of lending during financial crises when they have a higher ESG score. This finding is consistent with the literature showing that traditional banking activities are more stable over time due to higher switching and information costs and lower correlation with the business cycle than non-interest activities (such as trading and commission and fee activities) (DeYoung and Roland, 2001; Lepetit et al., 2008a; Lepetit et al., 2008b; Meslier et al., 2014; Köhler, 2015). If such traditional banking-oriented institutions are more engaged with high ESG firms and relationship banking, we would expect them to be less affected by a decrease in lending during the turmoil.

We also perform some additional analyses and find that our results are mainly driven by the environmental pillar component of the ESG score. As awareness of environmental issues progressively increases, it is not surprising that this component has the highest impact on lending in turbulent times (Azmi et al., 2021). Considering the strategic role banks play in funding environmental impact projects, investors are more likely to favor banks that focus on environmental issues such as climate change and air pollution. Next, we explore the environmental pillar further by considering the firm-level climate risk exposure indices developed by Sautner et al. (2023). We observe that overall lending falls during crisis times but to a greater extent for banks with higher climate change exposures, risks, and negative sentiment. We also disentangle the financial crisis periods (GFC in 2007–2009 and the European sovereign debt crisis in 2010–2012). Our results mainly hold during the GFC period.

Our paper contributes to the literature in several ways. First, we contribute to the recently emerging field of research (Cornett et al., 2016; Chiaramonte et al., 2022; Broadstock et al., 2021) on the impact of ESG on bank performance in crisis times and provide further insights by documenting that banks with higher ESG engagement are less negatively affected in terms of lending during turbulent times. Such banks are, hence, better able to perform their intermediation function when the economy strongly needs such support. We also show that banks are better armed to fund the economy during turmoil when they are better prepared for climate change challenges. Second, we further contribute to the strand of literature that documents the stabilizing effects of sustainability considerations in times of crisis in different financial settings. While this literature has focused on direct finance, such as, for example, equity markets (Ding et al., 2021; Capelle-Blancard and Desrozier, 2020), and mutual funds (Pástor and Vorsatz, 2020; Nofsinger and Varma, 2014), we look into indirect finance and specifically on bank

intermediation by investigating bank lending. Third, we focus on European banks as an empirical context. European banks have pioneered sustainability implementations compared to those headquartered in other regions (Ho et al., 2012; Chiaramonte et al., 2022). In line with the rising importance of climate change and growing evidence of its financial impact on banks, there have been significant regulatory developments in Europe to improve non-financial information and diversity disclosure. For instance, the Non-Financial Reporting Directive (2014/95/EU) took effect in 2014, and banking stress tests started to include climate-related risks in 2022. Fourth, we provide deeper insights into the channels of how ESG engagement might help banks to be less negatively impacted during crisis times.

Our findings have important implications that support the regulatory initiatives regarding improved disclosures on non-financial reporting. Better standards for ESG disclosures are increasingly helpful for financial decisions, and governments and regulators need to focus on the proliferation of policies and standards. The rest of the paper is organized as follows. Section 2 presents the data, variables, and the approach we use for our empirical investigation. Section 3 discusses the empirical findings, and Section 4 provides conclusions and policy implications.

## 2. Data, variables, and methodology

### 2.1. Data sources and sample

We focus on publicly listed commercial banks headquartered in Europe. ESG-related bank-level data are taken from the Refinitiv ASSET4 database. We restrict our sample to banks with annual ESG-related data available for at least three consecutive years between 2002 and 2020.<sup>4</sup> This leaves us with a sample of 83 publicly listed commercial banks from 20 European countries.<sup>5</sup> We then extract individual bank-level balance sheet and income statement data for these 83 banks from Refinitiv Datastream. We check for consistency of the extracted data with two other databases Bureau van Dijk (BVD) Bankscope and BVD Orbis BankFocus.<sup>6</sup> The data regarding country controls are from the World Bank World Development Indicators and the World Bank Global Financial Development Databases.

### 2.2. Variables

A brief description of variables, data sources, and summary statistics are presented in Table 1. We present our sample distribution by country in Table A.1 in the Appendix.

#### 2.2.1. Dependent variables

The main dependent variable to measure lending activity is the logarithm of the yearly growth rate of total loans (*LOANGRW*). For robustness, we also use the change in loans to total assets ratio calculated as the year-to-year difference of total loans normalized by total assets at the beginning of the period ( $\Delta LOANS_{TA}$ ). Table 1 indicates that the average lending growth in our sample is 5.26%.

#### 2.2.2. ESG variables

ESG-related variables are extracted from the Refinitiv ASSET4 database, which contains scores that measure a company's environmental, social, and governance performance and commitment since

<sup>4</sup> We start the sample in 2002 because ESG scores are not available prior to that year.

<sup>5</sup> These countries are Austria, Belgium, Cyprus, Czech Republic, Denmark, Finland, France, Georgia, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Romania, Spain, Sweden, and the United Kingdom.

<sup>6</sup> BankScope is replaced by BankFocus by Bureau van Dijk starting in 2017. Bankscope has data available until 2014.

**Table 1**  
Variable descriptions and summary statistics.

Variable	Description	Data sources	Obs	Mean	Min	Max	Median	Stand. Dev.
<b>Dependent variables</b>								
<i>LOANGRW</i>	The yearly logarithmic growth rate of total loans, $\ln(1 + (\text{Total loans at time } t - \text{Total loans at time } t-1) / \text{Total loans at time } t-1)$ .	Refinitiv Datastream	1286	8.53	-34.97	99.45	4.32	19.64
$\Delta$ <i>LOANS_TA</i>	The year-to-year difference of the total loans normalized by total assets at the beginning of the period.	Refinitiv Datastream	1236	5.28	-25.76	55.98	2.43	12.47
<i>LLP</i>	The ratio of loan loss provisions to gross loans.	Refinitiv Datastream	1296	0.96	-0.62	6.44	0.63	1.14
<i>SDROA</i>	It is the standard deviation of <i>ROA</i> , calculated using three-year rolling windows.	Refinitiv Datastream	1131	0.54	0.01	7.37	0.24	1.05
<i>INT EXPENSE</i>	The ratio of interest expense on deposits to total deposits.	Refinitiv Datastream	1245	0.02	0.00	0.13	0.02	0.02
<i>INT INCOME</i>	The share of interest income on loans to total loans.	Refinitiv Datastream	1229	0.04	0.00	0.14	0.04	0.02
<i>ROA</i>	Return on assets.	Refinitiv Datastream	1200	0.99	-5.78	5.81	0.95	1.29
<i>TOTAL LIABILITIES</i>	The ratio of total liabilities to total assets.	Refinitiv Datastream	1412	0.91	0.16	1.00	0.93	0.10
<i>DEPOSITS</i>	The ratio of deposits to total assets.	Refinitiv Datastream	1232	53.16	4.53	88.81	52.73	18.78
<i>MARKET FUNDING</i>	The ratio of market funding to total assets. We calculate market funding as the share of total assets funded by non-deposit liabilities, i.e., (total liabilities- shareholders equity- total deposits)/ total assets.	Refinitiv Datastream	1346	0.40	0.03	0.93	0.40	0.21
$\Delta$ <i>TOTAL ASSETS</i>	The annual change in total assets normalized by average total assets in the current and previous years.	Refinitiv Datastream	1326	7.48	-25.93	63.97	5.29	14.69
<b>ESG variables</b>								
<i>ESG</i>	ESG Combined Score is an overall company score which is the weighted average of the ESG score (relative sum of the three pillars (environmental, social, and governance)) and ESG controversy score. Ranges from 0 to 100.	Refinitiv ASSET4	1034	49.05	1.57	89.74	49.93	19.50
<i>ESG CHANGE</i>	The annual percentage change in the ESG score.	Refinitiv ASSET4	950	3.65	-59.61	71.72	2.63	22.78
<i>ENV</i>	Environmental pillar score shows banks' environmental performance, and it is a weighted sum of the following three categories: resource use score, emissions score, and innovation score. Ranges from 0 to 100.	Refinitiv ASSET4	1034	47.37	0	97.56	52.39	33.43
<i>GOV</i>	Governance pillar score represents the governance performance, and it is a weighted sum of the following three categories: management score, shareholders score, and CSR strategy score. Ranges from 0 to 100.	Refinitiv ASSET4	1034	54.18	1.88	97.37	57.29	24.76
<i>SOC</i>	Social pillar score is a weighted sum of the following four categories: workforce score, human rights score, community score, and product responsibility score. Ranges from 0 to 100.	Refinitiv ASSET4	1034	54.72	0.68	97.32	58.92	23.66
<i>ESG RELEVANCE</i>	ESG Relevance Scores show whether firms are sufficiently compensated for the level of ESG credit risk exposure. Scores range from 1 to 5, with higher scores showing greater materiality of ESG impact on the credit rating.	Fitch Connect	1045	3.83	3.80	4.00	3.80	0.07
<i>BUZZ</i>	Buzz score is a proxy for media attention, which delivers the number of ESG-relevant references to a given asset company in the media.	MarketPsych ESG Analytics	1160	1817.67	16.00	9292.00	287.00	3052.78
<i>ESG MARKETPSYCH</i>	ESG Combined score from MarketPsych adjusts ESG scores for greenwashing in case of a high level of ESG controversies.	MarketPsych ESG Analytics	1160	43.32	5.00	86.00	44.00	15.71
<i>Climate change exposure</i>	Measures the frequency with which certain climate change bigrams occur in the transcripts of earning calls, scaled by the total number of bigrams in the transcript. They count the number of such bigrams and divide by the total number of bigrams in the transcripts.	<a href="#">Sautner et al. (2023)</a>	689	22.17	0.00	252.44	16.13	27.53
<i>Climate change risk</i>	Counts the relative frequency of climate change bigrams mentioned together with the words "risk" or "uncertainty" in one sentence in the transcripts of earnings conference calls.	<a href="#">Sautner et al. (2023)</a>	689	1.88	0.00	61.01	0.00	5.86
<i>Climate change positive sentiment</i>	Whether the events represent (in expectation) good news to the firm. Relative frequency with which climate change bigrams are stated together with	<a href="#">Sautner et al. (2023)</a>	689	7.56	0.00	125.47	0.00	14.98

(continued on next page)

Table 1 (continued)

Variable	Description	Data sources	Obs	Mean	Min	Max	Median	Stand. Dev.
<i>Climate change negative sentiment</i>	positive tone words in the earnings conference call transcripts. Whether the events represent (in expectation) bad news to the firm. Relative frequency with which climate change bigrams are declared together with the negative tone words.	Sautner et al. (2023)	689	-5.52	-76.63	0.00	0.00	11.18
<b>Control Variables</b>								
<i>SIZE</i>	Natural logarithm of total assets.	Refinitiv Datastream	1412	18.50	10.88	23.87	18.30	2.07
<i>CAPITAL</i>	The ratio of bank equity to total assets.	Refinitiv Datastream	1262	20.11	1.38	97.87	16.89	13.67
<i>NPL</i>	Non-performing loans to gross loans.	Refinitiv Datastream	1123	6.79	0.05	59.82	3.57	9.85
<i>COVID</i>	A binary indicator that equals one for 2020 and zero otherwise.	Authors' calculations	1577	0.05	0	1	0	0.22
<i>CRISIS</i>	A binary indicator that equals one for 2007–2012 that captures both the global financial crisis of 2007–2009 and sovereign debt crisis of 2010–2012; and zero otherwise.	Authors' calculations	1577	0.26	0	1	0	0.44
<i>CRISIS 2008</i>	A binary indicator that equals one for the global financial crisis of 2007–2009; and zero otherwise.	Authors' calculations	1577	0.11	0.00	1.00	0.00	0.31
<i>CRISIS DEBT</i>	A binary indicator that equals one for sovereign debt crisis of 2010–2012; and zero otherwise.	Authors' calculations	1577	0.16	0.00	1.00	0.00	0.36
<i>GDPGRW</i>	Annual GDP per capita growth.	World Bank WDI	1577	1.24	-11.25	24.00	1.47	3.64
<i>CONCENTRATION</i>	5-bank asset concentration, calculated as the total assets of the three largest banks as a share of the total assets of the entire bank universe in the country.	World Bank GFDD	1560	65.65	0.00	100.00	75.93	31.41
<i>INFLATION</i>	The annual growth rate of the GDP implicit deflator.	World Bank WDI	1577	2.23	-4.67	23.15	1.85	2.36
<b>Instrumental variables</b>								
<i>CO2 EMISSIONS</i>	Country level yearly CO2 emissions (metric tons per capita).	World Bank ESG Database	1411	7.04	0.74	13.76	7.52	2.25
<i>GENDERDIV</i>	Gender diversity on the board at the bank level. The share of female directors in the board.	Refinitiv ASSET4	1010	19.44	0.00	61.54	17.65	14.57
<b>Other variables</b>								
<i>NII</i>	The share of noninterest income in total income at the bank level.	Refinitiv Datastream	1341	32.04	3.45	73.02	30.61	13.78
<i>ESG MANDATORY DISCLOSURE</i>	Equals 1 for the country and year when the mandatory disclosure is in effect (the effective year and onwards) in the corresponding country and 0 otherwise.	Krueger et al. (2021)	1425	0.39	0.00	1.00	0.00	0.49
<i>CDS SPREAD</i>	The 5-year sovereign CDS spread in the corresponding country.	Refinitiv Datastream	1063	1.24	0.02	12.32	0.67	1.89
<i>POST-PARIS INVESTOR PROTECTION</i>	Ranges from 0 to 10. Investor protection index shows the legal protection for investors in different countries.	Authors' calculations	1577	0.32	0.00	1.00	0.00	0.46
<i>ADRI</i>	Ranges from 0 to 6. ADRI employs six elements to measure the ease with which investors can exercise their rights in response to opportunistic behavior	World Bank	728	6.03	3.00	8.30	6.00	1.30
<i>ASDI</i>	Ranges from 0 to 1. ASDI shows the protection of minority investors against expropriation by corporate insiders. It encapsulates both the strength of anti-self-dealing laws and their enforcement.	La Porta et al. (1998)	1116	2.81	0.00	5.00	3.00	1.48
<i>BANKING CRISIS</i>	An indicator variable, taking a value of 1 if there is a banking crisis in that year in the corresponding country, 0 otherwise.	Djankov et al. (2008)	1314	4.67	1.81	9.50	4.21	2.45
<i>MOST AFFECTED COUNTRIES</i>	An indicator variable that equals 1 for the six most affected European countries from the financial crisis, which are Greece, Spain, Ireland, Cyprus, Portugal, and Italy; 0 otherwise.	Behavioral Finance & Financial Stability Project, Harvard Business School	928	0.41	0.00	1.00	0.00	0.49
		Authors' calculations	1577	0.34	0.00	1.00	0.00	0.47

Note: This table presents variables used in our empirical analyses, their brief descriptions, data sources, and summary statistics.

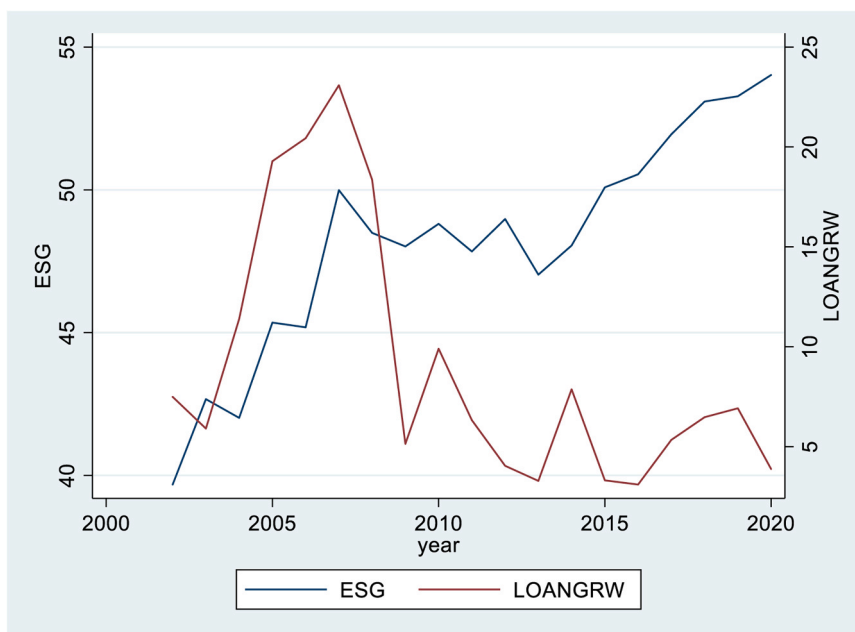
2002. These scores are calculated by content research analysts trained to collect ESG data, and they are based on publicly reported company-level data such as annual company reports and corporate social responsibility reports, stock exchange filings, and the news media. The scores are grouped into ten categories<sup>7</sup> that form the three pillar scores (environmental, social, and governance) and the combined score.<sup>8</sup> This paper uses

the combined ESG score (*ESG*), which ranges from 1 to 100. For robustness, we also use the change in ESG score (*ESG CHANGE*) calculated as the annual percentage change in the ESG score. We observe in Table 1 that the average *ESG* in our sample is 49.05, with a standard deviation of 19.50, showing a high variability.

Fig. 1 shows the behavior of *ESG* and *LOANGRW* between 2002 and 2020. We take the yearly averages of the variables to generate the series. Fig. 1 shows that there is a strong decrease in lending during crisis times for the years between 2008 and 2012, covering both the GFC and the sovereign debt crisis. Moreover, after both crises, lending has grown less than it had in the three years before the GFC. Meanwhile, although the crisis years show a slowdown, there is an overall improvement in the

<sup>7</sup> The ten categories for the three pillars are explained in Table 1.

<sup>8</sup> ESG Combined Score is an overall company score which is the weighted average of the ESG score (relative sum of the environmental, social, and governance pillars) and ESG controversy score.



**Fig. 1. The behavior of ESG and loan growth through time.** Note: This figure shows the time-series behavior of the variables *ESG* and *LOANGRW* between 2002 and 2020. We take the yearly averages of the variables to generate the series in the figure. The variables are generated from our sample of 83 listed banks from 20 European countries. *LOANGRW* is the average annual growth rate of total loans, and *ESG* is the average overall company score based on the environmental, social, and corporate governance pillars, respectively.

average ESG scores of banks in our sample, consistent with the progressive increase in the awareness of environmental and social issues among banks.

In our additional analysis, we explore whether the components of ESG scores differently affect lending during crisis times. For this purpose, we use the three pillars of ESG scores. Specifically, the environmental pillar score (*ENV*) captures reported environmental performance and commitment regarding resource use, emissions, and innovation. The governance pillar score (*GOV*) shows the governance-related information capturing the commitment to following best practice corporate governance principles and the effectiveness of equal treatment of shareholders. The social pillar score (*SOC*) considers workplace, human rights, community, and product responsibility-related activities. All indices range from 1 to 100. Table 1 shows that the average scores of *GOV* (54.18) and *SOC* (54.72) are higher than those of *ENV* (47.37). The standard deviation of *ENV* is also higher (33.43) than those of *GOV* and *SOC* (24.76 and 23.66, respectively), indicating a higher variation in the environmental performance scores of major banks in Europe.

### 2.2.3. Control variables

We control for a range of bank and country-level variables following the extant literature on the determinants of bank lending (Kim and Sohn, 2017; Ananou et al., 2021; Bilgin et al., 2021). Bank-level controls include the differences in bank size (*SIZE*)<sup>9</sup> calculated as the natural logarithm of total assets, the share of non-performing loans in gross loans (*NPL*), and differences in capitalization (*CAPITAL*) calculated as the ratio of bank equity to total assets.

To account for differences in macroeconomic environments and banking markets, as country-level controls, we use GDP growth

<sup>9</sup> As can be seen in Table 2, *SIZE* is highly correlated with *ENV*. To deal with this, we repeat our estimations, orthogonalizing the *SIZE* variable with *ENV*. We also replace the continuous size variable with an indicator variable that equals 1 for banks whose size is greater than the median. Our findings continue to hold in these specifications. The findings are available upon request.

(*GDPGRW*), measured as annual GDP per capita growth,<sup>10</sup> the inflation rate (*INFLATION*), and bank concentration (*CONCENTRATION*), calculated as the total assets of the five largest banks as a share of the total assets of the entire bank universe in the country (Danisman and Demirel, 2019).

Table 2 presents the correlation coefficients among the independent variables in the baseline estimations, indicating no major collinearity issues.

### 2.3. Methodology

Our regressions are conducted using yearly panel data estimations for the sample of 83 publicly listed commercial banks from 2002 to 2020. We explore the relationship between ESG activities and bank lending during crisis times in an empirical setting accounting for potential endogeneity issues. Following Wintoki et al. (2012) and Chiaromonte et al. (2022), we use the system generalized method of moments (GMM) estimator built by Blundell and Bond (1998) and Arellano and Bover (1995) with Windmeijer-corrected standard errors (Windmeijer, 2005) to account for endogeneity.<sup>11</sup>

System GMM combines the first differences with the level form, i.e., the regressions are estimated in levels and first differences simultaneously. The method reduces any biases and imprecision that would be associated with the first difference GMM. Meanwhile, it controls for heterogeneous endogeneity that might result from time-invariant variables. It captures the dynamic structure of the relationship between bank lending, ESG activity, and the crisis. Therefore, since the System GMM methodology can handle dynamic relationships, in our setting, which focuses on loan growth, it is expected to be superior to standard panel data techniques such as Fixed and Random Effects models. We consider

<sup>10</sup> We obtain similar findings when we use annual GDP growth instead of annual GDP per capita growth. The results are available upon request.

<sup>11</sup> As a robustness check, we also use a bank fixed-effects panel data regression model (as confirmed by the Hausman test) by clustering the standard errors at the bank level. Our results are available upon request, and they are broadly in line with the GMM findings.

**Table 2**  
Correlations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) ESG	1												
(2) ESG CHANGE	0.1831 *	1											
(3) ENV	0.7209 *	-0.0456	1										
(4) GOV	0.7136 *	0.0665 *	0.4561 *	1									
(5) SOC	0.8292 *	0.0201	0.7973 *	0.5614 *	1								
(6) NPL	-0.0663 *	-0.0286	-0.0493	-0.1511 *	-0.0898 *	1							
(7) CAPITAL	-0.1481 *	0.0084	-0.1267 *	-0.1720 *	-0.2026 *	-0.1632 *	1						
(8) SIZE	0.4148 *	-0.0706 *	0.5404 *	0.4065 *	0.5091 *	-0.2601 *	-0.1213 *	1					
(9) GDPGRW	-0.0681 *	0.033	-0.1529 *	-0.002	-0.0824 *	-0.0302	-0.0021	-0.028	1				
(10) CONCENTRATION	-0.0694 *	-0.0132	-0.0671 *	-0.0768 *	-0.1334 *	-0.0303	0.0924 *	0.0158	0.1647 *	1			
(11) INFLATION	-0.056	0.0165	-0.0935 *	0.0209	-0.0115	-0.2407 *	0.0403	-0.0272	0.3433 *	-0.0189	1		
(12) CRISIS	-0.0192	-0.0358	0.0536	-0.0131	-0.0378	-0.0919 *	0.0293	0.0161	-0.2536 *	0.2161 *	-0.049	1	
(13) COVID	0.0634 *	0.0134	0.0693 *	0.0207	0.0852 *	0.0094	-0.0374	0.0244	-0.4974 *	-0.4956 *	0.0402	-0.1409 *	1

Note: This table displays the correlation matrix for the variables that are used in our baseline analysis, \* indicates significance at 0.05.

the lagged dependent variable as endogenous and the rest of the explanatory variables as exogenous. We use the second and higher order lags and differences of the dependent variable as instruments to address endogeneity resulting from including the lagged dependent variable as an explanatory variable. We keep the number of instruments smaller than the number of groups (Roodman, 2009). We test for over-identifying restrictions using the Hansen test and also test for first-order and second-order autocorrelation.

Our baseline specification to test the effects of ESG on bank lending in crisis times is as follows:

$$LOANGRW_{i,t} = LOANGRW_{i,t-1} + \beta_1 CRISIS_t + \beta_2 ESG_{i,t-1} * CRISIS_t + \beta_3 ESG_{i,t-1} + \beta_4 COVID_t + \theta X_{i,t-1} + \vartheta Y_{j,t-1} + \alpha_j + \varepsilon_{it} \quad (1)$$

where i stands for banks, j for countries, and t for years. All explanatory variables are lagged by one year to alleviate any potential reverse causality problems. Our main dependent variable is *LOANGRW*. We include the first lag of *LOANGRW* as an explanatory variable because first-order autocorrelation is present in the error terms. *ESG* stands for overall bank-level ESG scores. *CRISIS* is a binary indicator that equals one between 2007 and 2012, capturing both the GFC (2007–2009) and the European sovereign debt crisis (2010–2012) and zero otherwise. Considering that all European countries in our sample were more or less affected by both the GFC and the sovereign debt crisis, we use these same years as crisis times for every country in the sample. Since some EU countries were affected more by the sovereign debt crisis, we use alternative crisis indicators at the country level, which are presented in robustness checks. These two crises have originated in the credit markets and are rooted in the financial sector, which has led to a broad distrust in financial firms. Meanwhile, the COVID-19 pandemic started from public health concerns, not due to economic conditions (Albuquerque et al., 2020), and it should be treated differently from the two financial crises. But, the potential negative impact of COVID-19 on bank lending also needs to be controlled in the estimations. For this purpose, we include the binary indicator variable, *COVID*, in Eq. 1, which equals 1 for the year 2020 and 0 otherwise.

We include the interaction variable *ESG\*CRISIS* in Eq. 1 to explore the influence of ESG during crisis times. Our coefficient of interest is  $\beta_1 + \beta_2$ , i.e., the sum of the coefficients of the *ESG\*CRISIS* and the *CRISIS* variables. A negative and significant  $\beta_1 + \beta_2$  and positive and significant  $\beta_2$  would show that lending falls for all banks in the sample during the crisis but to a significantly lesser extent for higher ESG banks. X stands for bank-level control variables and Y for country controls. We use country-fixed effects that diminish omitted variable problems, such as differences in macroeconomic conditions, policy applications, and accounting and regulatory practices.

### 3. Results

#### 3.1. Baseline results

The baseline findings are displayed in Table 3. The regressions are estimated using the two-step system GMM estimators. As argued above, the first lags of explanatory variables are used to mitigate any potential reverse causality issues. Robust-Windmeijer corrected standard errors are given in parentheses. Country-fixed effects are included in all specifications. At the bottom of the table, we report the Hansen test p-values, and the insignificance of the statistics confirming the validity of the instruments. Moreover, we provide AR(2) second-order autocorrelation tests at the bottom of the table, the insignificance of the statistics showing no second-order serial correlation in the error terms.

Model 1 presents the baseline estimations and uses *LOANGRW* as the dependent variable. The sum of the coefficients of *CRISIS* ( $\beta_1$ ) and *ESG\*CRISIS* ( $\beta_2$ ) presented at the bottom of the table is significant and negative at the 1% level. Meanwhile, the coefficient of the interaction term  $\beta_2$  is positive and significant at the 1% level, indicating that ESG

**Table 3**  
Effect of ESG on Bank lending- Baseline Estimations.

	(1) Baseline	(2) $\Delta LOANS\_TA$	(3) ESG CHANGE	(4) HIGH ESG	(5) LOW ESG	(6) POSITIVE ESG CHANGE	(7) NEGATIVE ESG CHANGE
ESG	0.043 (0.04)	0.018 (0.01)					
CRISIS ( $\beta_1$ )	-11.939*** (2.98)	-5.348*** (1.36)	-3.378*** (0.76)	-2.756*** (0.45)	-4.727*** (1.19)	-1.786** (0.83)	-4.963*** (1.53)
ESG *CRISIS ( $\beta_2$ )	0.164*** (0.05)	0.050** (0.02)					
ESG CHANGE			-0.025 (0.02)				
ESG CHANGE *CRISIS ( $\beta_3$ )			0.220*** (0.08)				
COVID	-4.707*** (1.18)	-2.215*** (0.57)	-4.038*** (1.26)	-4.187*** (1.21)	-5.304* (2.80)	-3.332* (1.68)	-5.384*** (0.98)
NPL	-0.205*** (0.06)	-0.231*** (0.04)	-0.199*** (0.06)	-0.112*** (0.02)	-0.298*** (0.04)	-0.156*** (0.05)	-0.245** (0.10)
CAPITAL	-0.132*** (0.05)	-0.009 (0.02)	-0.092* (0.05)	-0.060** (0.03)	-0.081** (0.04)	-0.078** (0.03)	-0.023 (0.10)
SIZE	-2.657*** (0.96)	-1.304** (0.65)	-0.958 (0.74)	-0.934*** (0.21)	-1.948*** (0.45)	-1.237*** (0.25)	-2.239*** (0.51)
GDPGRW	0.359** (0.14)	-0.017 (0.04)	0.273* (0.15)	0.423*** (0.14)	-0.274*** (0.09)	0.068 (0.14)	0.424 (0.27)
CONCENTRATION	0.016 (0.02)	0.006 (0.01)	0.009 (0.02)	0.023* (0.01)	0.006 (0.02)	0.021 (0.02)	-0.010 (0.01)
INFLATION	-0.509* (0.27)	-0.010 (0.15)	-0.969*** (0.33)	-0.410*** (0.13)	-0.155 (0.22)	-0.620** (0.25)	-0.872** (0.39)
L. $\Delta LOANS\_TA$		0.405*** (0.04)					
L.LOANRGRW	0.392*** (0.04)		0.431*** (0.05)	0.656*** (0.04)	0.338*** (0.04)	0.440*** (0.05)	0.210** (0.08)
Constant	54.996*** (13.64)	27.259** (12.69)	21.940* (12.10)	21.319*** (3.59)	44.763*** (8.94)	31.264*** (5.67)	52.589*** (11.41)
$\beta_1 + \beta_2$	-11.775***	-5.298***					
$\beta_1 + \beta_3$			-3.158***				
Country FE	YES	YES	YES	YES	YES	YES	YES
Number of observations	774	765	718	550	408	668	290
Number of banks	75	74	73	41	36	77	62
Number of instruments	60	83	59	40	31	58	57
Hansen p-value	0.174	0.803	0.421	0.510	0.957	0.161	0.247
AR (2)	0.382	0.507	0.128	0.089	0.485	0.805	0.375

Note: This table presents the baseline regression findings for the impact of ESG activity on bank lending in crisis times. We use a sample of 83 listed banks from 20 European countries and yearly data for the period 2002–2020. We implement the two-step system GMM dynamic panel data estimation techniques. The first lags of explanatory variables are used to mitigate any potential reverse causality. Country-fixed effects are used in all models. The dependent variable is the annual growth rate of total loans,  $LOANRGRW$ , in all models except for Column 2. Column 2 uses  $\Delta LOANS\_TA$  as an alternative dependent variable calculated as the ratio of the year-to-year difference of the total loans normalized by total assets at the beginning of the period. Column 3 uses an alternative ESG proxy,  $ESG\_CHANGE$  ( $ESG\_CHANGE$ ), calculated as the annual percentage change in the ESG score. Columns 4 and 5 use subsamples and HIGH ESG indicates the subsample of banks whose ESG score is above the median ( $>49.93$ ) and LOW ESG below the median, respectively. Columns 6 and 7 use subsamples, and POSITIVE ESG CHANGE indicates the subsample of banks whose  $ESG\_CHANGE$  is greater than zero, and NEGATIVE ESG CHANGE indicates the subsample of banks whose  $ESG\_CHANGE$  is smaller than zero, respectively. Variable definitions can be found in Table 1. Windmeijer corrected standard errors are used when clustering the error terms and are given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

activity mitigates, to some extent, the fall in bank lending during crisis periods. In terms of economic magnitude, a one-standard-deviation increase (19.50) in  $ESG$  in crisis times mitigates the decrease in bank lending by 3.2% ( $19.50 * 0.164\%$ ), and the overall decrease in bank lending corresponds to  $-8.74\%$  ( $-11.939\% + 3.2\%$ ).<sup>12</sup> Model 2 uses an alternative dependent variable,  $\Delta LOANS\_TA$ , and Model 3 uses an alternative ESG proxy,  $ESG\_CHANGE$ . Our results continue to hold in both models 2 and 3. Models 4 and 5 are estimated on subsamples. HIGH ESG stands for the subsample of banks whose ESG score is above the median ( $>49.93$ ), and LOW ESG for the subsample of banks with an ESG score below the median. We continue to implement the two-step system GMM dynamic panel data estimation techniques. While the coefficients of CRISIS are negative and significant for both subsamples, the

<sup>12</sup> As a further investigation, we decompose our dependent variable, loan growth, into loan types, which are commercial, consumer, and mortgage loan growth. We find that ESG activity mitigates the fall in bank lending during crisis periods for all three types of loans. The results are available upon request.

magnitude of the negative impact of the crisis on bank lending is higher for the subsample of banks whose ESG score is lower, providing additional support for earlier findings.

Models 6 and 7 in Table 3 use two subsamples: POSITIVE ESG CHANGE and NEGATIVE ESG CHANGE. POSITIVE ESG CHANGE indicates positive changes in ESG ratings, and we select the subsample of banks whose  $ESG\_CHANGE$  is greater than zero. NEGATIVE ESG CHANGE indicates the subsample of banks whose  $ESG\_CHANGE$  is smaller than zero. We find that while the coefficients of CRISIS are negative and significant for both subsamples, the magnitude of the negative impact of the crisis on bank lending is higher for banks whose change in ESG score is negative. Such banks with negative changes in their ESG ratings are more severely affected by crises in terms of their lending.

We also consider unexpected and large changes in ESG scores and explore how such banks are affected. We perform subsample estimations and construct the POSITIVE ESG CHANGE subsample as banks whose  $ESG\_CHANGE$  is larger than the 90% percentile and NEGATIVE ESG CHANGE as banks whose  $ESG\_CHANGE$  is smaller than the 10%

percentile. Our findings continue to hold, i.e., while both subsamples of banks are negatively affected in terms of lending during crises, banks with an unexpected negative change in their ESG rating are more severely affected by crises. Our findings are not tabulated due to space considerations but are available upon request.

On the whole, overall lending falls during crisis times but to a lesser extent for banks with higher ESG scores. Such banks normally have a larger base of borrowing firms highly engaged in ESG themselves (Houston and Shan, 2022; Hasan et al., 2022); hence, our results could be explained by the quality of bank borrowers during crisis times. Indeed, in line with Godfrey (2005), El Ghouli et al. (2011), and El Ghouli and Karoui (2017), ESG firms actually benefit from ESG investments specifically in terms of lower idiosyncratic risk and agency costs during crises, such banks should have a better ability to maintain their lending relationships and support their borrowers. Our finding is also in line with the findings of recent studies that document the positive impact of CSR on bank efficiency (Belasri et al., 2020), bank value (Azmi et al., 2021), and bank stability (Chiaromonte et al., 2022).

Considering the impact of control variables, we observe that they generally have the expected signs. Specifically, bank lending is negatively associated with increased credit risk as proxied by higher non-performing loans. This aligns with prior evidence documenting the significant negative correlation between credit risk and bank lending behavior (Stepanyan and Guo, 2011; Ananou et al., 2021). Higher capitalization is negatively associated with bank lending. Specifically, banks might shrink their assets to meet higher capital levels, which would decrease the availability of bank lending (Hanson et al., 2011; Fang et al., 2020). We find that larger banks tend to have lower loan growth. This is in line with the notion that large banks can better achieve diversification in their asset portfolios. Thus, they are likely to hold less loans relative to total assets (Demsetz and Strahan, 1997). Small banks are better at collecting and acting on soft information than large banks, and large banks might be less willing to lend to firms with no financial records, leading to less lending overall (Berger and Black, 2011). Moreover, our findings indicate that bank lending is higher for countries with higher GDP per capita growth and lower inflation. Finally, lending falls during the COVID-19 pandemic, as would be expected.

### 3.2. Instrumental variable estimations

While reverse causality concerns are mitigated in our estimations by including lagged independent variables in our regressions, there are other potential sources of endogeneity, such as omitted variables. Hence, in addition to dynamic panel data estimation with the two-step system GMM estimators, we use instrumental variable (IV) regressions with two-stage least squares (2SLS) estimators to further address potential endogeneity concerns. In this setting, the ESG variable is taken as endogenous, but finding a potentially exogenous instrument for such a variable is a challenging task. A strong and valid instrument should not directly influence the dependent variable (bank lending) other than through its indirect effect on the endogenous variable (ESG variable). Based on the extant literature on CSR and ESG, we use four potential instruments to address endogeneity.

First, following prior studies (Azmi et al., 2021; Bose et al., 2021; among others), we use the previous year's ESG score to instrument ESG performance. The previous year's ESG score is likely positively correlated with the current ESG score. Second, following Ioannou and Serafeim (2012), Cheng et al. (2014), and Azmi et al. (2021), we use an average country-level ESG rating. Ioannou and Serafeim (2012) show that CSR is determined by country characteristics and that a firm's CSR is impacted by a time-varying component at the country level. We would expect the country-level ESG score to be positively correlated with the current ESG score. However, it is not clearly evident that the country-level ESG scores would directly affect bank lending.

Third, recent literature suggests that CSR activities around the location of the firm are positively associated with firms' CSR activities

through knowledge spillovers and institutional pressures (Husted et al., 2016; Bardos et al., 2020). In this spirit, following Bardos et al. (2020), we use CO2 emissions (metric tons per capita) (*CO2 EMISSIONS*) in the country where the bank is headquartered, stemming from the burning of fossil fuels and the manufacturing of cement. We collect this data from the World Bank Environmental Social and Governance (ESG) Database. We expect banks located in countries in which CO2 emissions are higher to have a lower ESG score.

Fourth, following Cornett et al. (2016), we use gender diversity on the board (*GENDERDIV*) as an instrumental variable. *GENDERDIV* is calculated as the total number of female directors divided by the total number of board members. *GENDERDIV* is an ex-ante theoretically plausible instrument because gender diversity and ESG practices are likely to be highly positively correlated. There is a consensus in the literature that firms' sustainability performance is expected to increase with more women on the board (Gillan et al., 2021). The literature has indeed shown that a higher share of women on boards is positively associated with charitable contributions, climate change and environmental impact concerns, and reputation-based CSR measures (Williams, 2003; Zhang et al., 2013). However, it is not evident in the literature why gender diversity would be directly correlated to bank lending, although some papers argue that it could affect the riskiness of loans (Berger et al., 2014; Karavitis et al., 2021). We perform specification tests to validate the relevance and strength of our instruments.<sup>13</sup>

Table 4 presents the findings of the instrumental variable estimations for the impact of ESG activity on bank lending in crisis times. Columns 1 and 2 present the first and second-stage findings for the instrumental variable analysis when ESG is taken as endogenous, and it is instrumented by the country mean of ESG scores (*COUNTRY ESG*) and previous year ESG score (*L.ESG*). The first stage equation in Column 1 uses ESG as the dependent variable. The two instruments for ESG and other control variables are used to estimate the predicted ESG for each bank. We use panel data estimation techniques with bank fixed effects in Column 1 and implement the two-step system GMM dynamic panel data estimation techniques in Column 2, respectively. In Column 1, we observe the expected positive and significant impacts of *COUNTRY ESG* and *L.ESG* on ESG. Next, in Column 2, the predicted ESG ( $\widehat{ESG}$ ) is included. Column 2 shows that the sum of the coefficients of *CRISIS* and  $\widehat{ESG} * CRISIS$  is negative and significant at the 1% level, while the coefficient of the interaction term keeps its significance and positive sign, confirming previous findings. The instrument's validity is tested using the F-statistic for the instrumental variable, which is 286 and significant at the 1% level, well above the weak instrument criteria, i.e., critical values (Stock and Yogo, 2005).<sup>14</sup> Columns 3 and 4 present the first and second-stage findings of the instrumental variable estimations when we use CO2 emissions (metric tons per capita) as an instrument (*CO2 EMISSIONS*). In Column 3, we observe the expected negative and significant impact of *CO2 EMISSIONS* on ESG. Column 4 shows that the sum of the coefficients of *CRISIS* and  $\widehat{ESG} * CRISIS$  is negative and significant at the 1% level, confirming previous findings. Columns 5 and 6 present the first and second-stage findings when we use gender diversity on the

<sup>13</sup> We also try the introduction of ESG mandatory disclosures as an alternative instrumental variable. We thank our anonymous referee for this suggestion. The introduction of mandatory ESG disclosure is expected to be positively correlated with the ESG ratings of banks. We use a novel publicly available dataset on mandatory ESG disclosures around the world from Krueger et al. (2021) and generate a dummy variable, "ESG MANDATORY DISCLOSURE," which equals 1 for the year when the mandatory disclosure is in effect in the corresponding country and 0 otherwise. We use *ESG MANDATORY DISCLOSURE* to instrument ESG performance and perform IV regressions with two-stage least squares (2SLS) estimators. We find that our baseline findings continue to hold. The results are available upon request.

<sup>14</sup> The critical value for the Cragg–Donald statistic for 10% maximal size distortion is 19.93.

**Table 4**  
Instrumental Variable Estimations.

	(1) IV First stage	(2) IV Second stage	(3) IV First stage	(4) IV Second stage	(5) IV First stage	(6) IV Second stage
$\widehat{ESG}$		-0.009 (0.06)		0.087 (0.10)		0.194** (0.09)
COUNTRY ESG	0.636*** (0.05)					
L. ESG	0.425*** (0.03)					
CO2 EMISSIONS			-1.109* (0.60)			
GENDERDIV					0.186*** (0.04)	
CRISIS ( $\beta_1$ )	-0.941 (0.82)	-12.248*** (4.18)	-0.935 (1.03)	-17.898*** (5.83)	-0.268 (1.09)	-12.112** (5.99)
$\widehat{ESG} * CRISIS$ ( $\beta_2$ )		0.198** (0.08)		0.286** (0.11)		0.187* (0.11)
COVID	2.123 (1.92)	-4.091*** (1.19)	0.000 (.)		3.464 (2.44)	-4.763*** (1.28)
NPL	-0.034 (0.05)	-0.242*** (0.05)	0.142* (0.07)	-0.191*** (0.06)	0.142** (0.06)	-0.189*** (0.06)
CAPITAL	0.093* (0.05)	-0.068 (0.05)	0.137* (0.07)	-0.133** (0.06)	0.185*** (0.07)	-0.167*** (0.06)
SIZE	3.637*** (0.98)	-1.849** (0.80)	9.989*** (1.29)	-3.523** (1.40)	9.239*** (1.21)	-3.531*** (1.00)
GDPGRW	0.151 (0.13)	0.329** (0.13)	0.123 (0.18)	0.261* (0.14)	0.138 (0.17)	0.339** (0.15)
CONCENTRATION	0.007 (0.01)	0.012 (0.02)	-0.069*** (0.02)	0.010 (0.02)	-0.045*** (0.02)	0.024 (0.02)
INFLATION	0.289 (0.24)	-0.652*** (0.23)	-0.469 (0.32)	-0.361 (0.31)	-0.229 (0.30)	-0.579* (0.32)
L.LOANGRW		0.361*** (0.05)		0.408*** (0.05)		0.432*** (0.04)
Constant	-72.507*** (17.46)	36.590*** (12.56)	-124.339*** (27.14)	70.008*** (20.38)	-117.360*** (21.63)	62.056*** (14.07)
$\beta_1 + \beta_2$		-12.05 * *		-17.612 * * *		-11.925 * * *
Country FE	YES	YES	YES	YES	YES	YES
Bank FE	YES	NO	YES	NO	YES	NO
R2 Adjusted	0.7824		0.6727		0.6269	
Number of observations	781	718	721	708	821	754
Number of banks	75	73		71		75
Number of instruments		59		57		60
Hansen p-value		0.270		0.10		0.163
AR (2)		0.117		0.273		0.554
F Statistic	286.00 * * *		133.7 * *		177.7 * * *	

Note: This table presents the instrumental variable analysis findings for the impact of ESG activity on bank lending in crisis times. We use a sample of 83 listed banks from 20 European countries and yearly data for the period 2002–2020. The dependent variables are *ESG* in Columns 1, 3, and 5 (for the first-stage estimations) and *LOANGRW* in Columns 2, 4, and 6 (for the second-stage estimations), respectively. *ESG* variable is taken as endogenous. Columns 1 and 2 present the first and second stage findings for the instrumental variable analysis when the *ESG* variable is instrumented by country mean of ESG scores (*COUNTRY ESG*) and previous year ESG score (*L.ESG*). Columns 3 and 4 present the instrumental variable estimations' first and second stage findings when we use the instrument: CO2 emissions (metric tons per capita) (*CO2 EMISSIONS*). Columns 5 and 6 present the first and second stage findings of the instrumental variable estimations when we use the following instrument: gender diversity on the board (*GENDERDIV*). Except for Columns 1, 3, and 5, we implement the two-step system GMM dynamic panel data estimation techniques. Columns 1, 3, and 5 use panel data estimation techniques with bank and country fixed effects. The first lags of explanatory variables are used to mitigate any potential reverse causality. Windmeijer corrected standard errors are used when clustering the error terms and given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

board as an instrument (*GENDERDIV*). Again, we still obtain the expected positive and significant impact of *GENDERDIV* on *ESG*. Column 6 shows that the sum of the coefficients of *CRISIS* and  $\widehat{ESG} * CRISIS$  is negative and significant at the 1% level, confirming previous findings.

### 3.3. Difference-in-difference analysis

In this section, we utilize a difference-in-differences framework where we estimate the difference in the lending behavior of ESG-rated banks between the pre-crisis and crisis periods with the same difference in behavior of a matched control group of banks without an ESG rating. Initially, in our paper, we restrict our sample to banks with annual ESG-related data available for at least three consecutive years between 2002 and 2020, which gives us a sample of 83 publicly listed commercial banks from 20 European countries. To generate the control group, we extract from Refinitiv Datastream data on listed banks

without ESG ratings in the same 20 countries. Specifically, we extract data for 57 banks without ESG ratings in 20 European countries. To match the treated and the control banks, we use a group of banks without ESG ratings that share the characteristics of our treated banks with ESG ratings prior to financial crises. We use propensity score matching to account for potential selection bias (Roberts and Whited, 2013). We first run a logit model to calculate propensity scores using all bank-level control variables (*SIZE*, *NPL*, *CAPITAL*) for the period before the financial crises (2002–2006). We match, without replacement, each treated bank to a control bank using the nearest three neighbors (Chang et al., 2019; Ananou et al., 2021). We next perform the DiD regression on the resulting matched sample using the following ordinary least square (OLS) model with bank-fixed effects over the period 2002–2012:

$$LOANGRW_{i,t} = \beta_1 SHOCK_t + \beta_2 ESGRATED_{i,t-1} * SHOCK_t + \beta_3 ESGRATED_{i,t-1} + \theta X_{i,t-1} + \vartheta Y_{i,t-1} + \alpha_i + \varepsilon_{it} \quad (2)$$

where *ESGRATED* is a binary variable that equals 1 for banks with ESG ratings and 0 for those without ESG ratings. *SHOCK* is a binary indicator that equals one between 2007 and 2012, capturing both the GFC (2007–2009) and the European sovereign debt crisis (2010–2012) and zero during the pre-crisis period, 2002–2006. *X* stands for bank-level control variables, and *Y* for country controls as in baseline estimations.

Panel A in Table 5 displays the logit model's findings that are used to calculate propensity scores. Our logit model includes a binary dependent variable, *ESGRATED*, bank-level controls, and bank-fixed effects. Panel B in Table 5 presents the t-tests of the matched sample during the pre-financial crisis period (2002–2006). We observe no significant differences between treated (ESG-rated) and control groups (non-ESG-rated) in the matched sample before the crises. This confirms that control banks are very similar to treatment banks during the pre-crisis period, reducing individual differences and potential bias. Panel C in Table 5 shows the t-tests of the matched sample during the crisis period (2007–2012). We observe significant differences between treated and control groups for most variables. Specifically, the loan growth (*LOANGRW*) of the treated group (10.59%) is significantly higher than that of the control group (4.99%) during the crises. Panel D in Table 5 displays the results of the DiD regression. The coefficient of the interaction term *ESGRATED*\**SHOCK* is significantly positive, supporting our baseline results. As a whole, lending falls to a lesser extent for banks with ESG ratings as compared to banks without such ratings being available.

### 3.4. Channel analysis

In this section, we investigate the possible reasons why, during crisis times, banks with higher ESG scores decrease lending to a lesser extent than banks with lower ESG scores. We test for potential channels and explore the impact of ESG on bank risk, banks' pricing behavior, and the components of their balance sheets in crisis times. For this purpose, we estimate the following set of equations:

$$Y_{i,t} = Y_{i,t-1} + \beta_1 CRISIS_t + \beta_2 ESG_{i,t-1} * CRISIS_t + \beta_3 ESG_{i,t-1} + \beta_4 COVID_t + \theta X_{i,t-1} + \vartheta Y_{i,t-1} + \alpha_j + \varepsilon_{it} \quad (3)$$

where  $Y_{i,t}$  stands for various outcome channel variables, and the rest of the variables are as in Eq. 1, except for bank-level controls ( $X_{i,t-1}$ ). Bank-level controls are adjusted to reflect the change in our dependent variables; they now include only *SIZE* and *CAPITAL*; *NPL* is excluded as a control.

To explore the impact of ESG scores on bank risk as a potential channel, we consider the influence of ESG on credit risk measures such as the ratio of non-performing loans to gross loans (*NPL*) and the ratio of loan loss provisions to gross loans (*LLP*). We also look at asset risk more generally by using the standard deviation of the return on assets (*ROA*) calculated using three-year rolling windows (*SDROA*).

To investigate the impact of ESG scores on pricing behavior, we take as proxies the implicit interest rate on loans measured as the interest income on loans to total loans (*INTINC*) and the implicit rate on deposits measured as the interest expenses on deposits to total deposits (*INTEXP*). We also consider how profitability is affected by using *ROA* as the dependent variable. Eventually, we also look at whether ESG scores influence the structure of balance sheets during crises. Specifically, we consider the ratio of total liabilities to total assets (*TOTAL LIABILITIES*), the share of total deposits in total assets (*DEPOSITS*), the ratio of market funding to total assets (*MARKET FUNDING*), and change in total assets ( $\Delta$  *TOTAL ASSETS*), respectively. We calculate *MARKET FUNDING* as the share of assets funded by non-deposit liabilities, i.e., total liabilities excluding equity & total deposits, divided by total assets (Brei et al., 2013).

Table 6 displays the channel analysis findings regarding bank risk. Models 1–3 use the following dependent variables: *NPL*, *LLP*, and

**Table 5**

Difference-in-difference estimation.

Panel A – Logit model: identifying propensity scores				
	(1) <i>ESGRATED</i>			
<i>NPL</i>	0.224 * (0.16)			
<i>CAPITAL</i>	-0.007 (0.02)			
<i>SIZE</i>	1.432 * ** (0.245)			
Constant	-23.139 * ** (3.97)			
Number of observations	251			
Bank FE	YES			
LR chi2 test	151.85 * **			
Pseudo R2	0.7234			
Panel B – T-tests of the matched sample during the pre-financial crises period (2002–2006).				
Variables	Treated	Control	Difference	p-values
<i>LOANGRW</i>	15.27	12.46	2.81	0.467
<i>NPL</i>	1.01	1.22	-0.20	0.521
<i>CAPITAL</i>	17.71	23.41	-5.70	0.115
<i>SIZE</i>	16.10	16.06	0.04	0.879
Panel C – T-tests of the matched sample during the crises period (2007–2012).				
Variables	Treated	Control	Difference	p-values
<i>LOANGRW</i>	10.59	4.99	5.60	0.0590
<i>NPL</i>	3.92	2.78	1.14	0.0857
<i>CAPITAL</i>	19.04	27.40	-8.36	0.0004
<i>SIZE</i>	16.53	16.26	0.26	0.1754
Panel D – Difference-in-difference analysis				
Dependent variable	(1) <i>LOANGRW</i>			
<i>ESGRATED</i>	-3.343 (2.89)			
<i>SHOCK</i>	-6.030 ** (1.90)			
<i>ESGRATED</i> * <i>SHOCK</i>	5.634 ** (5.21)			
<i>NPL</i>	-2.517 ** (1.02)			
<i>CAPITAL</i>	0.063 (0.14)			
<i>SIZE</i>	-1.200 (1.40)			
<i>GDPGRW</i>	0.387 * * (0.27)			
<i>CONCENTRATION</i>	0.021 (0.08)			
<i>INFLATION</i>	1.256 (1.93)			
Constant	29.862 (24.65)			
Number of observations	105			
R2	0.2079			
Bank FE	YES			

Notes: This table displays the results of the differences-in-differences estimation. Panel A uses a logit model for the propensity score matching (PSM) procedure. The dependent variable, *ESGRATED*, is a binary variable that equals 1 for banks with available ESG ratings and 0 for those without ESG ratings. Panel B provides the t-tests of the matched sample pre-financial crisis period (2002–2006). Panel C shows the t-tests of the matched sample during the crisis period (2007–2012). Panel D presents the results of the DiD estimation for an OLS estimation with bank-fixed effects. *SHOCK* is a binary indicator that equals one between 2007 and 2012, capturing both the GFC (2007–2009) and the European sovereign debt crisis (2010–2012) and zero during the pre-crisis period, 2002–2006. Standard errors in parentheses \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

*SDROA*, respectively. The sums of the coefficients of *CRISIS* and *ESG*\**CRISIS* ( $\beta_1 + \beta_2$ ) are positive and significant at the 1% level in all models. Meanwhile, the coefficients of *CRISIS* ( $\beta_1$ ) are positive and significant at the 1% level, and the coefficients of *ESG*\**CRISIS* ( $\beta_2$ ) are

**Table 6**  
Channels Estimations-The impact on bank risk.

	(1) <i>NPL</i>	(2) <i>LLP</i>	(3) <i>SDROA</i>
<i>ESG</i>	-0.005 (0.01)	-0.003** (0.00)	-0.002*** (0.00)
<i>CRISIS</i> ( $\beta 1$ )	1.241*** (0.34)	0.370*** (0.07)	0.172*** (0.02)
<i>ESG</i> * <i>CRISIS</i> ( $\beta 2$ )	-0.018*** (0.01)	-0.002* (0.00)	-0.001** (0.00)
Constant	-9.402** (4.09)	-1.420** (0.71)	0.696** (0.31)
$\beta 1 + \beta 2$	1.223 * **	0.368 * **	0.171 * **
Country FE	YES	YES	YES
Controls	YES	YES	YES
Number of observations	778	846	767
Number of banks	76	80	75
Number of instruments	59	60	68
Hansen p-value	0.589	0.206	0.136
AR (2)	0.839	0.893	0.205

Note: This table presents the regression findings for channel analysis regarding the impact of ESG on bank risk in crisis times. We use a sample of 83 listed banks from 20 European countries and yearly data for the period 2002–2020. We implement the two-step system GMM dynamic panel data estimation techniques. The first lags of explanatory variables are used to mitigate any potential reverse causality. Country fixed effects are used in all models. Models 1 and 2 use the following dependent variables: the ratio of non-performing loans to gross loans (*NPL*) and the ratio of loan loss provisions to gross loans (*LLP*). Model 3 uses *SDROA*, which is the standard deviation of *ROA* calculated using three-year rolling windows. Windmeijer corrected standard errors are used when clustering the error terms and given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

negative and significant. This indicates that while all the banks in our sample exhibit higher credit risk (i.e., *NPL* and *LLP*) and asset risk (i.e., *SDROA*) in crisis times, banks with higher ESG scores are less affected. Hence, the fact that banks with higher ESG can more easily pursue their lending activities during crises is possibly driven by their lower exposure to asset and credit risk. Indeed, according to the stakeholder theory, ESG investments lower the perceived riskiness of firms and reduce agency and information asymmetry problems (Godfrey, 2005; El Ghoul et al., 2011; El Ghoul and Karoui, 2017). Because higher ESG banks are more involved in high ESG firms for their lending activities, consistently, their risk should be less affected during crisis times and, consequently, their

**Table 7**  
Channels Estimations- Effects on the pricing and the components of the balance sheet.

	(1) <i>INT EXPENSE</i>	(2) <i>INT INCOME</i>	(3) <i>ROA</i>	(4) <i>TOTAL LIABILITIES</i>	(5) <i>DEPOSITS</i>	(6) <i>MARKET FUNDING</i>	(7) $\Delta$ <i>TOTAL ASSETS</i>
<i>ESG</i>	-0.0000 (0.00)	-0.0000 (0.00)	-0.0006 (0.00)	-0.0001*** (0.00)	0.0121 (0.01)	-0.0006*** (0.00)	-0.0313** (0.01)
<i>CRISIS</i> ( $\beta 1$ )	0.043*** (0.00)	0.004 (0.00)	-0.4890*** (0.11)	-0.037** (0.00)	-0.5280 (0.66)	-0.0183*** (0.00)	-3.0267*** (0.87)
<i>ESG</i> * <i>CRISIS</i> ( $\beta 2$ )	-0.001*** (0.00)	0.000* (0.00)	0.0048*** (0.00)	0.001* (0.00)	-0.0070 (0.01)	0.006*** (0.00)	0.0304* (0.02)
Constant	-0.0067 (0.01)	0.0253** (0.01)	3.0602*** (0.65)	-0.0174 (0.02)	7.5779* (4.30)	-0.0678* (0.04)	8.4468*** (0.86)
$\beta 1 + \beta 2$	0.042 * **	0.004	-0.4842 * **	-0.036 * *	-0.535	-0.0123 * **	-2.9963 * **
Country FE	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES
Number of observations	810	811	818	873	838	924	852
Number of banks	77	78	80	82	81	81	81
Number of instruments	59	60	60	60	41	73	63
Hansen p-value	0.1580	0.1506	0.1187	0.5676	0.3850	0.6314	0.4045
AR (2)	0.068	0.9279	0.6514	0.0607	0.0234	0.9381	0.2739

Note: This table presents the regression findings for channel analysis regarding the impact of ESG on bank pricing and the components of the balance sheet in crisis times. We use a sample of 83 listed banks from 20 European countries and yearly data for the period 2002–2020. We implement the two-step system GMM dynamic panel data estimation techniques. The first lags of explanatory variables are used to mitigate any potential reverse causality. Country fixed effects are used in all models. Models 1–7 use the following dependent variables: interest expense on deposits to total deposits (*INTEXP*), interest income on loans to total loans (*INTINC*), return on assets (*ROA*), the ratio of total liabilities to total assets (*TOTAL LIABILITIES*), the share of total deposits in total assets (*DEPOSITS*), the ratio of market funding to total assets (*MARKET FUNDING*), and change in total assets ( $\Delta$  *TOTAL ASSETS*) respectively. Windmeijer corrected standard errors are used when clustering the error terms and given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

lending.

Table 7 presents the findings regarding implicit rates on loans and deposits, profitability, and balance sheet structure. Models 1–2 consider *INTEXP* and *INTINC* as dependent variables. The coefficient of  $\beta 1 + \beta 2$  displayed at the bottom of the table is significant and positive for *INTEXP* but not significant for *INTINC*. This indicates that while implicit deposit rates increase in crisis times, the increase is lower for banks with higher ESG scores. Meanwhile, the crisis has no significant impact on the implicit interest rate on loans regardless of how much banks are involved in ESG activities. This indicates that depositors of banks with higher ESG scores require a lower increase in interest rates during turmoil, possibly because they are more confident than depositors in banks with lower ESG scores. This finding is in line with Azmi et al. (2021), who find a positive relationship between ESG and the net interest margin of emerging market banks. Higher ESG banks are perceived to be more transparent and less risky by investors in crisis times. Their depositors might be more tolerant of lower interest rate premia in exchange for better environmental performance. This finding is also consistent with the predictions of the theoretical model of Albuquerque et al. (2019). In times of crisis, ESG activity helps banks differentiate their products, generate a more loyal customer base, and advance to lower price elasticity of demand.

Next, Models 3–7 investigate the impact of ESG on *ROA*, *TOTAL LIABILITIES*, *DEPOSITS*, *MARKET FUNDING*, and  $\Delta$  *TOTAL ASSETS*, respectively. The coefficients of  $\beta 1 + \beta 2$  are significantly negative, and the interaction terms are significantly positive for *ROA*, *TOTAL LIABILITIES*, *MARKET FUNDING*, and  $\Delta$  *TOTAL ASSETS*. This shows that while banks experience a fall in profitability, total liabilities, market funding, and total assets, in crisis times, banks with higher ESG scores are significantly less affected. They downsize to a lesser extent by presumably being less impacted by the fall in market funding. While the share of deposits in total liabilities remains unchanged for all banks during crisis times, ESG banks are able to limit the fall in their total assets possibly by borrowing more easily on the market, which allows them to cut lending to a lesser extent in crisis times.

Overall, our findings indicate that during crisis times, higher ESG banks decrease their lending to a significantly lesser extent, possibly because their credit and asset risk, profitability, and size are less affected than other banks. Banks with higher ESG involvement downsize their balance sheet to a lesser extent by borrowing more extensively on the

market than other banks. Moreover, their deposit cost increases to a lesser extent than the deposit cost of low ESG banks in crisis times. This is possibly because banks with higher ESG scores are perceived as more transparent, increasing depositors' trust (Azmi et al., 2021). The literature shows that banks fail to convince green bond investors, i.e., investors may not be able to identify a clear link between the green bond issued by a financial institution and a specific green investment project (Fatica et al., 2021). We find that banks with higher ESG performance are able to borrow cheaper and attract more deposits and short-term market funding. This is probably because while bonds correspond to longer-term financing, deposits and short-term market debt are shorter-term in their nature, enabling banks to more easily attract investors.

### 3.5. Further investigations

For further insights, in this section, we perform additional tests. We first consider the influence of bank business models on the impact of ESG activity on bank lending in crisis times. We next disentangle the impact of ESG activity on bank lending for the three ESG components and the different financial crisis periods.

#### 3.5.1. The effect of bank business models

In this section, we consider the influence of bank business models to investigate whether our findings originate from banks focused more on traditional intermediation activities (lending and deposits) or more diversified in their income structure. We present the findings in Table 8. Models 1 and 2 split banks into ones that have a higher and lower share of loans in total assets (*LTA*), greater than and smaller than the 75th and 25th percentile, respectively. Models 3 and 4 show the findings for banks whose loans to total assets ratio (*LTA*), and deposits to total assets ratio (*DepTA*) are simultaneously greater and smaller than their median values. Models 5 and 6 oppose relatively highly and lowly diversified banks by considering the median of the share of non-interest income in total income (*NI*). The sum of the coefficients of *CRISIS* ( $\beta_1$ ) and *ESG* \* *CRISIS* ( $\beta_2$ ) are only significantly negative, and  $\beta_2$  is significantly positive only in Models 1, 3, and 6. These are the subsamples of banks with a higher share of loans and deposits in total assets and a lower share of non-interest income in total income. Therefore, our results mainly originate from banks focused on traditional deposit and lending activities and less diversified into non-interest activities. Such banks are the least affected in terms of lending during financial crises when they have a higher ESG score.

This finding is consistent with the literature showing that traditional banking activities are more stable over time mainly because they are based on relationship banking. Such relationships are less easy to end because of switching and information costs. Meanwhile, non-interest income (from trading activities, and commission and fee activities) is highly correlated with the business cycle (DeYoung and Roland, 2001; Lepetit et al., 2008a; Lepetit et al., 2008b; Meslier et al., 2014; Köhler, 2015). When banks are more oriented towards traditional banking activities as well as towards higher ESG firms, they suffer less from a fall in lending during crises.<sup>15</sup>

#### 3.5.2. Disentangling the ESG components and the financial crisis periods

In this section, we first explore whether the components (the three pillars) of ESG scores differently affect lending during crisis times. We then disentangle the impact of ESG activity on bank lending for different crisis periods, i.e., the subprime crisis in 2007–2009 and the European

sovereign debt crisis in 2010–2012.

Table 9 provides the findings regarding ESG Components. We use the environmental pillar score (*ENV*), the governance pillar score (*GOV*), and the social pillar score (*SOC*) as independent variables of interest, respectively (Columns 1–3). For this purpose, we include the interaction terms *ENV* \* *CRISIS*, *GOV* \* *CRISIS*, and *SOC* \* *CRISIS* in the regressions. The sum of the coefficients of *CRISIS* and interaction terms (presented at the bottom of the table) are significantly negative, and the interaction term is significantly positive at the 1% level only for the environmental pillar but not for the other components.

Therefore, our main finding showing that banks are able to decrease their lending significantly less during turbulent times when they are more engaged in ESG activities is essentially driven by the environmental pillar. This result is in line with Azmi et al. (2021) and Chiramonte et al. (2022), who find that the environmental pillar component has the greatest positive effect on bank value and stability, respectively. As attention towards global warming and the transition to sustainability has been progressively increasing, investors could be more concerned regarding banks' consideration of environmental matters in turbulent times. They would be more likely to prefer banks that focus and act on environmental issues when there is more uncertainty (Azmi et al., 2021; Chiramonte et al., 2022). Moreover, our channel analysis has shown that, during crises, banks with higher ESG scores are able to access market funding and attract depositors at a lower cost. Hence, because they can raise resources more easily than banks with lower ESG ratings, possibly due to a preference of depositors and investors to the environmental dimension than to the two other pillars, banks with higher ESG ratings are likely to cut their lending to a lesser extent during crises.

Our finding that the environmental pillar matters more is also in line with other recent literature, which finds that the environmental sub-pillar outperforms all other sub-pillars in terms of risk reduction in banking (Meles et al., 2023), and it has the most significant impact on mitigating firms' default likelihood (Palmieri et al., 2023). Liu et al. (2023) also find that a bank's environmental pillar performance drives the negative association with non-performing loans. Thus, the environmental pillar being associated with higher risk reduction, lower borrower default, and lower non-performing loans, would help banks to decrease their lending significantly less during turmoil times.

To investigate whether it is only the environmental pillar that matters, we also consider the impact of the ESG components on the lending of banks with different business models during crisis times. Our findings show that banks focused on traditional deposit and lending activities and less diversified into non-interest activities and with higher environmental (*ENV*) and social scores (*SOC*) exhibit a significantly lower reduction in lending. Therefore, both environmental and social scores matter for banks that are more oriented toward traditional banking activities during turmoil.<sup>16</sup>

As we show that our main finding is essentially driven by the environmental pillar, we next explore the environmental pillar further by taking into account the climate risk exposure indices developed by Sautner et al. (2023). Sautner et al. (2023) introduce a database that has various indices on firm-level climate change exposures/risks/sentiments, indicating the occurrence of climate change events or shocks at the firm. They are calculated from earnings conference call conversations, using quarterly earnings calls to identify firms' various risks and opportunities. We use ISIN codes in their dataset to match those against our bank-level dataset. Most of the banks in our dataset are covered by their database; thereby, we can extract bank-level climate change exposures/risks/sentiment indices. We utilize the following four equally weighted indices from their dataset: climate change exposure, climate change risk, climate change positive sentiment, and climate change negative sentiment. The climate change exposure index measures the frequency with which certain climate change bigrams occur in the

<sup>15</sup> As a further investigation, we investigate the influence of bank size. We split banks into large and small banks with total assets greater and smaller than the sample median. We find that ESG activity mitigates the fall in bank lending during crisis periods, mainly for larger banks. The results are available upon request.

<sup>16</sup> The results are available from the authors on request.

**Table 8**

Additional analysis: the effect of bank business models.

	(1) <i>LTA</i> > 75 <sup>th</sup> percentile	(2) <i>LTA</i> < 25 <sup>th</sup> percentile	(3) <i>LTA</i> > Median & <i>DepTA</i> > Median	(4) <i>LTA</i> < Median & <i>DepTA</i> < Median	(5) <i>NII</i> > Median	(6) <i>NII</i> < Median
<i>ESG</i>	-0.070*** (0.01)	0.071 (0.06)	-0.062** (0.03)	0.061 (0.04)	0.022* (0.01)	-0.040*** (0.01)
<i>CRISIS</i> ( $\beta_1$ )	-6.092*** (1.00)	-1.277 (10.06)	-8.959*** (2.63)	-3.567 (4.56)	-4.844* (2.53)	-9.622*** (1.35)
<i>ESG</i> * <i>CRISIS</i> ( $\beta_2$ )	0.040** (0.02)	-0.002 (0.17)	0.106** (0.05)	0.040 (0.08)	0.054 (0.04)	0.090*** (0.03)
Constant	30.338*** (3.73)	19.436 (17.58)	39.937*** (5.07)	29.564* (15.63)	44.459*** (2.99)	24.074*** (1.54)
$\beta_1 + \beta_2$	-6.052 * **	-1.275	-8.853 * **	-3.527	-4.79 *	-9.532 * **
Country FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Number of observations	212	204	235	258	422	352
Number of banks	47	28	49	32	58	64
Hansen p-value	0.824	0.998	0.567	0.996	0.387	0.357
AR (2)	0.756	0.442	0.411	0.941	0.279	0.840

Note: This table presents additional tests and the regression findings for business model analysis for the impact of ESG activity on bank lending in crisis times. We use a sample of 83 listed banks from 20 European countries and yearly data for the period 2002–2020. We implement the two-step system GMM dynamic panel data estimation techniques. The first lags of explanatory variables are used to mitigate any potential reverse causality. Country fixed effects are used in all models. The dependent variable is the annual growth rate of total loans, *LOANGRW*, in all models. Models 1 and 2 report the baseline regression findings for banks whose share of total loans in total assets (*LTA*) are greater and smaller than the 75th percentile (*LTA* > 75.22%) and 25th percentile (*LTA* < 57.14%), respectively. Models 3 and 4 report the baseline regression findings for banks whose share of loans in total assets (*LTA*) and the share of deposits in total assets (*DepTA*) are both greater and smaller than their median values, respectively. The median *LTA* and *DepTA* in our sample stand at 66.78% and 52.73%, respectively. Models 5 and 6 report the baseline regression findings for banks whose share of noninterest income in total income (*NII*) are greater and smaller than the median value (30.61%), respectively. Windmeijer corrected standard errors are used when clustering the error terms and given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 9**

Additional analysis- ESG pillars.

	(1) <i>ENV</i>	(2) <i>GOV</i>	(3) <i>SOC</i>
<i>ENV</i>	-0.018 (0.02)		
<i>CRISIS</i> ( $\beta_1$ )	-7.045*** (1.83)	-3.405* (1.90)	-6.123** (2.61)
<i>ENV</i> * <i>CRISIS</i> ( $\beta_2$ )	0.069** (0.03)		
<i>GOV</i>		0.053** (0.02)	
<i>GOV</i> * <i>CRISIS</i> ( $\beta_3$ )		0.010 (0.03)	
<i>SOC</i>			-0.036 (0.04)
<i>SOC</i> * <i>CRISIS</i> ( $\beta_4$ )			0.048 (0.04)
Constant	50.928*** (15.86)	56.920*** (7.79)	43.821*** (16.38)
$\beta_1 + \beta_2$	-6.976 * **		
$\beta_1 + \beta_3$		-3.395 *	
$\beta_1 + \beta_4$			-6.075 * **
Country FE	YES	YES	YES
Controls	YES	YES	YES
Number of observations	774	774	774
Number of banks	75	75	75
Number of instruments	60	75	60
Hansen p-value	0.159	0.416	0.147
AR (2)	0.354	0.414	0.394

Note: This table presents the regression findings for the impact of ESG components (environmental pillar (*ENV*), governance pillar (*GOV*), and social pillar (*SOC*) scores) on bank lending in crisis times. We use a sample of 83 listed banks from 20 European countries and yearly data for the period 2002–2020. We implement the two-step system GMM dynamic panel data estimation techniques. The dependent variable is the annual growth rate of total loans, *LOANGRW*, in all models. The first lags of explanatory variables are used to mitigate any potential reverse causality. Country fixed effects are used in all models. Windmeijer corrected standard errors are used when clustering the error terms and given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

transcript, scaled by the total number of bigrams in the transcript. The climate change risk index counts the relative frequency of climate change bigrams mentioned together with “risk” or “uncertainty” in the same sentence. Climate change positive and negative sentiment indices differ on the basis of whether the events represent (in expectation) good or bad news to the firm. For normalizing purposes, we multiply these four indices by 100,000 and include them in our regressions one at a time. We present our findings in Table A.2 in the Appendix. We observe that overall lending falls during crisis times but to a greater extent for banks with higher climate change exposures, higher climate change risks, and climate change negative sentiment. We do not find any significant difference for banks that are more exposed to climate change positive sentiment. This shows that climate change exposures and risks, as well as negative sentiment, matter for bank lending during crisis times. Banks that are more exposed to climate change exposures, risks, and negative sentiment face a greater decrease in their lending during crisis times, supporting previous findings.

Table 10 considers the different financial crisis periods separately. Models 1 and 2 look at whether the relationship differs between the subprime crisis in 2007–2009 and the European sovereign debt crisis in 2010–2012. For this purpose, we use two dummy variables, *CRISIS 2008* and *CRISIS DEBT*. *CRISIS 2008* takes the value of 1 from 2007 to 2009 and 0 otherwise, and *CRISIS DEBT* takes the value of 1 from 2010 to 2012 and 0 otherwise. We interact these variables with *ESG*. While the sum of the coefficients of the crisis term and the *ESG* variable is significantly negative for these two periods, the interaction term coefficient is only positive and significant for the case of the 2007–2009 subprime crisis. Our findings are hence mainly driven by the GFC.<sup>17</sup> Considering the two crises separately by introducing each of the three pillars

<sup>17</sup> Even though the COVID-19 period is not a financial crisis and despite the fact that our focus is specifically on financial crisis, we also look at whether the COVID-19 pandemic has any separate influence by interacting *ESG* and COVID. We find the interaction term’s coefficient insignificant, suggesting that the mitigating effect of *ESG* on lending does not operate during the pandemic. Note that such a finding is not reliable and could be due to an insufficient number of observations to cover the pandemic and its aftermath. The findings are not tabulated but are available upon request.

**Table 10**  
Additional analysis- Disentangling the financial crisis periods.

	(1) CRISIS 2008	(2) CRISIS DEBT
ESG	0.070* (0.04)	0.081** (0.04)
CRISIS 2008 ( $\beta_1$ )	-17.329*** (4.48)	-5.022*** (0.96)
ESG * CRISIS 2008 ( $\beta_2$ )	0.237*** (0.09)	
CRISIS DEBT ( $\beta_3$ )	-2.629*** (0.69)	-3.668* (1.99)
ESG * CRISIS DEBT ( $\beta_4$ )		0.022 (0.03)
COVID ( $\beta_5$ )	-4.824*** (1.18)	-4.938*** (1.18)
ESG * COVID ( $\beta_6$ )		
Constant	55.561*** (14.02)	54.398*** (14.07)
$\beta_1 + \beta_2$	-17.092 ***	
$\beta_3 + \beta_4$		-3.646 *
$\beta_5 + \beta_6$		
Country FE	YES	YES
Controls	YES	YES
Number of observations	774	774
Number of banks	75	75
Number of instruments	61	61
Hansen p-value	0.171	0.152
AR (2)	0.326	0.318

Note: This table presents additional tests and disentangles the impact of ESG activity on bank lending for different financial crisis periods, i.e., the subprime crisis in 2007–2009 and the European sovereign debt crisis in 2010–2012. We use a sample of 83 listed banks from 20 European countries and yearly data for the period 2002–2020. We implement the two-step system GMM dynamic panel data estimation techniques. The first lags of explanatory variables are used to mitigate any potential reverse causality. Country fixed effects are used in all models. The dependent variable is the annual growth rate of total loans, *LOANGRW*, in all models. *CRISIS 2008* takes a value of 1 for 2007–2009 and 0 otherwise, and *CRISIS DEBT* takes 1 for the years 2010–2012 and 0 otherwise. Windmeijer corrected standard errors are used when clustering the error terms and given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

(environmental (*ENV*), governance (*GOV*), social (*SOC*)) in the regressions still reveals that our findings mainly hold during GFC, with only the environmental pillar playing a significant role.<sup>18</sup> This might be because the subprime crisis had originated in the credit markets, and it is documented in the literature that banks with higher ESG scores were able to better differentiate their lending according to borrowers' ESG performance (Chen et al., 2021; Houston and Shan, 2022). Chen et al. (2021) find that banks with higher social responsibility account for their borrowers' social responsibility performance and charge higher loan spreads to borrowers with poor performance. Houston and Shan (2022) find that banks with strong ESG performance are more likely to lend to borrowers with better ESG ratings.

### 3.6. Further Robustness Checks

In this section, we perform various robustness checks. First, it is argued in the literature that ESG ratings may differ quite substantially across data providers, with sometimes a low correlation (Berg et al., 2022). To test whether our main findings are robust, we also consider bank-level ESG scores from two other data providers: FitchConnect and MarketPsych ESG Analytics. FitchConnect is a comprehensive bank financial data set from Fitch Ratings. It provides ESG Relevance Scores for Fitch-rated entities, providing a reliable way to evaluate whether firms are sufficiently compensated for their level of ESG credit risk exposure. Scores range from 1 to 5, with higher scores showing greater

materiality of ESG impact on the credit rating. We use the ESG Relevance score and present the findings in Column 1 of Table A.3 in the Appendix. Our baseline findings continue to hold, i.e., overall, lending falls during crisis times but to a lesser extent for banks with higher ESG relevance scores. The second alternative ESG data provider, MarketPsych ESG Analytics, applies real-time AI-based natural language processing and assesses ESG-related articles from a diverse array of news and social media sites globally. We use the Buzz score and ESG Combined score from MarketPsych. Buzz score is a proxy for media attention, and it delivers the number of ESG-relevant references to a given company in the media. Since the Buzz score is skewed, we take the natural logarithm of the score in our regressions. ESG Combined score of MarketPsych adjusts ESG scores for greenwashing in case of high-level ESG controversies. Columns 2 and 3 of Table A.3 in the Appendix present the findings using the Buzz and ESG Combined scores from MarketPsych. Our baseline findings continue to hold using these alternative ESG scores.

The introduction of mandatory ESG disclosures in a country might influence both banks' ESG ratings and the screening process of banks. Specifically, mandatory ESG disclosures may induce banks to select better borrowers, considering their ESG characteristics. Some countries in our sample have introduced ESG mandatory disclosures in the sample period at different times, and some have not. For example, mandatory ESG disclosure was in effect by the Parliament in France in 2001 and in 2009 in Belgium. To account for these country differences, we use a novel publicly available dataset on mandatory ESG disclosures around the world from Krueger et al. (2021). We retrieve the mandatory disclosure years for the countries in our dataset and generate a dummy variable, "*ESG MANDATORY DISCLOSURE*," which equals 1 for the year and after the mandatory disclosure is in effect in the corresponding country and 0 otherwise. Column 1 of Table A.4 in the Appendix presents our findings after controlling for ESG mandatory disclosures. Our baseline results continue to hold.

It might also be the case that the average borrower risk of banks with high vs. low ESG performance may differ due to macroeconomic/financial conditions in crisis times. One way of dealing with such an issue is to control for sovereign risk. As a proxy for sovereign risk, we extract Sovereign 5 yr CDS Spreads (bps) from Refinitiv Datastream and control for it in our baseline estimations. Column 2 of Table A.4 in the Appendix shows that our baseline findings continue to hold after controlling for sovereign CDS spreads.

We also check whether there is a Paris Agreement effect (Delis et al., 2019; Reghezza et al., 2022). Our findings might be driven by an increased attention to ESG factors and climate topics in the last years, especially after the Paris Agreement in 2015. To consider this, we include a dummy variable in the regressions for post-Paris Agreement years, *POST-PARIS*, taking a value of 1 for the years 2015–2020 and 0 otherwise. We add *POST-PARIS* as an additional control variable in our baseline regressions and present our findings in Column 3 in Table A.4 in the Appendix. Our baseline findings continue to hold after controlling for the Paris Agreement effect.<sup>19</sup>

It is documented in the literature that a country's stakeholder orientation and investor protection affect bank behavior and lending (La Porta et al., 2000; Belasri et al., 2020, among others). As a further robustness check, to control for different institutional stakeholder environments, we include the following three country-level variables: anti-director rights index (*ADRI*) (La Porta et al., 1998), anti-self-dealing-index (*ASDI*) (Djankov et al., 2008), and investor protection index (World Bank). Columns 4–6 of Table A.4 in the Appendix present the results. Our baseline findings continue to hold under these

<sup>18</sup> The results of these estimations are not displayed in the paper but are available on request.

<sup>19</sup> We also interact *POST-PARIS* with ESG in the baseline estimations and find the interaction term's coefficient to be insignificant, showing that the effect does not originate from the Paris Agreement. The findings are available upon request.

specifications.

Finally, we try alternative *CRISIS* variable definitions and present our findings in Table A.5 in the Appendix. First, we extract an indicator variable for banking crises by country from “Global Crises Data by Country” which is compiled by the Behavioral Finance & Financial Stability Project at Harvard Business School (<https://www.hbs.edu/behavioral-finance-and-financial-stability/data/Pages/global.aspx>).

Column 1 in Table A.5 uses *BANKING CRISIS* as an alternative crisis variable, which is an indicator variable, taking a value of 1 if there is a banking crisis in that year in the corresponding country and 0 otherwise. Our findings are robust when we use this alternative crisis variable. Column 2 uses baseline estimations, controlling for most affected countries. *MOST AFFECTED COUNTRIES* is an indicator variable for the six most affected European countries from the sovereign debt crisis, which are Greece, Spain, Ireland, Cyprus, Portugal, and Italy. Our results are consistent after controlling for most affected countries. In Columns 3 and 4, we dig deeper and use subsamples for the most affected countries vs. the rest. Our main findings originate not from the most affected countries (i.e., Greece, Spain, Ireland, Cyprus, Portugal, and Italy) but from the rest of the countries. This means that overall lending falls during crisis times but to a lesser extent for banks with higher ESG scores in the rest of the 14 European countries, which are not as much affected by the crises.

#### 4. Conclusion

This paper investigates the relationship between European banks’ environmental, social, and governance (ESG) activities and their lending during times of financial crisis. In our regressions, we employ a sample of 83 listed banks from 20 European countries for the 2002–2020 period and use dynamic panel data estimation techniques with the two-step system GMM estimators. We cover both the 2007–2009 global financial crisis (GFC) and the 2010–2012 European sovereign debt crisis. Our findings show that ESG activity mitigates to some extent the negative impact of crises on bank lending. Our results are robust to alternative specifications to address potential endogeneity issues (instrumental variables (IV) and difference-in-difference estimations). Our findings continue to hold using alternative ESG rating providers, controlling for the Paris Agreement, and controlling for time-varying country-level factors such as differences in mandatory ESG disclosures, sovereign risk,

country’s stakeholder orientation, and investor protection. Deeper investigations show that such a finding is mostly driven by banks focused on traditional activities, the environmental pillar component of ESG, and the global financial crisis of 2007–2009.

Our channel investigations show that higher ESG banks also suffer from a lower increase in credit risk and overall asset risk. They also experience a lower fall in profitability than their peers. Moreover, the depositors of such banks request a lower increase in deposit rates in crisis times. Banks with higher ESG activity are also the ones that face a lower reduction in market funding, allowing them to downsize their balance sheets to a lesser extent during crises. Such findings suggest that, during crisis times, banks with higher ESG engagement appear to be more successful in efficiently allocating resources for both demanders and providers of capital. They are perceived to be less risky and possibly more transparent, increasing depositors’ trust. Such banks could, hence, also face a lower likelihood of runs.

Our findings reveal that improving ESG engagement in the banking sector is not only beneficial in terms of decreasing the environmental and social impacts but also helps to mitigate the reduction in bank lending during turbulent times. Banks play an essential role in the economy and, specifically, during crisis times when borrowers need them even more. However, during such episodes, banks are known to sharply reduce lending because of much higher default risk among borrowers. This prevents banks from efficiently performing their intermediation function and delays the time of economic recovery even more. Our findings suggest that ESG engagement could contribute to smoothening such ups and downs in financial intermediation and possibly reduce its cost for the economy in the long run by preserving long-term lending relationships.

Our findings also support the regulatory efforts in terms of better disclosures of non-financial information. Specifically, our findings support the recent regulatory changes in Europe brought by the Non-Financial Reporting Directive, requiring large banks to provide information on social and environmental practices and on how much they respect human rights or pay attention to diversity on their board of directors. As a future policy, regulatory bodies might need to consider how to extend these requirements to smaller financial institutions. Future research could explore how ESG performance affects bank lending in different industries, such as high-carbon versus low-carbon industries.

## Appendix

**Table A.1**  
Sample distribution by country.

Country	Number of banks	Number of observations	Average ESG	Average LOANGRW
AUSTRIA	3	57	47.13	10.81
BELGIUM	2	38	37.95	1.69
CYPRUS	1	19	32.49	-7.47
CZECH REPUBLIC	2	38	45.41	6.90
DENMARK	5	95	32.77	7.92
FINLAND	2	38	55.61	3.39
FRANCE	3	57	56.97	6.23
GEORGIA	1	19	44.44	20.66
GERMANY	5	95	51.73	2.21
GREECE	5	95	45.83	8.37
HUNGARY	1	19	51.97	15.48
IRELAND	3	57	45.38	0.09
ITALY	11	209	44.75	8.14
NETHERLANDS	2	38	65.25	-2.58
POLAND	10	190	42.30	14.40
PORTUGAL	2	38	56.46	1.51
ROMANIA	2	38	49.89	14.74
SPAIN	6	114	67.28	7.53
SWEDEN	5	95	56.74	5.43
UNITED KINGDOM	12	228	48.33	13.04
<b>Total</b>	<b>83</b>	<b>1577</b>	<b>49.05</b>	<b>8.53</b>

**Table A.2**

The impact of Climate Change Exposures.

	(1)	(2)	(3)	(4)
<i>CRISIS</i>	-2.661*** (0.98)	-1.531* (0.84)	-4.508*** (0.51)	-5.080*** (1.05)
<i>Climate change exposure</i>	0.042*** (0.01)			
<i>Climate change exposure* CRISIS</i>	-0.126** (0.06)			
<i>Climate change risk</i>		0.083* (0.04)		
<i>Climate change risk* CRISIS</i>		-0.331*** (0.12)		
<i>Climate change positive sentiment</i>			0.054* (0.03)	
<i>Climate change positive sentiment* CRISIS</i>			-0.004 (0.03)	
<i>Climate change negative sentiment</i>				0.052 (0.04)
<i>Climate change negative sentiment* CRISIS</i>				-0.119*** (0.03)
Constant	84.903*** (15.44)	48.516* (24.35)	77.457*** (14.21)	65.708*** (12.38)
Controls	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Number of observations	540	540	540	572
Number of banks	54	54	54	55
Number of instruments	57	44	47	47
Hansen p-value	0.636	0.999	0.693	0.361
AR (2)	0.124	0.990	0.130	0.175

Note: This table investigates the impact of bank-level climate risk exposure indices (instead of ESG scores) on bank lending in crisis times. We use climate risk exposure indices developed by Sautner et al. (2023). Columns 1–4 use climate change exposure, climate change risk, climate change positive sentiment, and climate change negative sentiment indices, respectively. We implement the two-step system GMM dynamic panel data estimation techniques. The first lags of explanatory variables are used to mitigate any potential reverse causality. Country-fixed effects are used in all models. The dependent variable is the annual growth rate of total loans, *LOANGRW*, in all models. Variable definitions can be found in Table 1. Windmeijer corrected standard errors are used when clustering the error terms and are given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table A.3**

Robustness Checks- Alternative ESG data providers.

	(1)	(2)	(3)
<i>ESG RELEVANCE</i>	-0.074 (0.56)		
<i>CRISIS</i>	-73.005** (29.05)	-6.516*** (1.82)	-4.640*** (0.81)
<i>ESG RELEVANCE *CRISIS</i>	1.747** (0.76)		
<i>BUZZ</i>		0.350 (0.63)	
<i>BUZZ *CRISIS</i>		0.601** (0.27)	
<i>ESG MARKETPSYCH</i>			0.058*** (0.01)
<i>ESG MARKETPSYCH *CRISIS</i>			0.050*** (0.02)
Constant	37.227 (23.92)	54.889*** (14.52)	33.291*** (2.35)
Controls	YES	YES	YES
Country FE	YES	YES	YES
Number of observations	689	849	849
Number of banks	51	69	69
Number of instruments	44	66	59
Hansen p-value	0.468	0.520	0.297
AR (2)	0.843	0.753	0.733

Note: This table presents the robustness findings for the impact of ESG activity on bank lending in crisis times, using alternative ESG data providers. We implement the two-step system GMM dynamic panel data estimation techniques. The first lags of explanatory variables are used to mitigate any potential reverse causality. Country-fixed effects are used in all models. The dependent variable is the annual growth rate of total loans, *LOANGRW*, in all models. Column 1 uses the ESG Relevance score of Fitch Connect, and Columns 2 and 3 use the Buzz score and ESG Combined score from MarketPsych ESG Analytics. Variable definitions can be found in Table 1. Windmeijer corrected standard errors are used when clustering the error terms and are given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table A.4**  
Robustness Checks- Controlling for country level factors.

	(1)	(2)	(3)	(4)	(5)	(6)
<i>ESG</i>	0.116*** (0.04)	0.003 (0.02)	0.073* (0.04)	0.047 (0.06)	-0.008 (0.03)	0.006 (0.03)
<i>CRISIS</i>	-10.827*** (3.01)	-4.485** (2.19)	-11.963*** (2.82)	-10.887*** (3.99)	-10.605*** (2.27)	-11.817*** (2.45)
<i>ESG *CRISIS</i>	0.126** (0.05)	0.079** (0.04)	0.147*** (0.05)	0.157** (0.07)	0.133*** (0.04)	0.149*** (0.05)
<i>ESG MANDATORY DISCLOSURE</i>	-3.349*** (0.93)					
<i>CDS SPREAD</i>		0.036 (0.19)				
<i>POST-PARIS</i>			-4.216*** (0.77)			
<i>INVESTOR PROTECTION</i>				-0.416 (0.35)		
<i>ADRI</i>					0.054 (0.29)	
<i>ASDI</i>						-0.041 (0.15)
<i>L.LOANGRW</i>	0.357*** (0.04)	0.186*** (0.07)	0.364*** (0.04)	0.333*** (0.08)	0.372*** (0.05)	0.383*** (0.05)
<i>Constant</i>	73.414*** (14.90)	28.762*** (5.00)	61.772*** (15.11)	56.076*** (8.34)	41.772*** (5.83)	39.325*** (6.12)
Country FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Number of observations	724	644	774	417	573	660
Number of banks	69	74	75	53	52	63
Number of instruments	59	39	61	28	40	40
Hansen p-value	0.219	0.204	0.230	0.656	0.242	0.196
AR (2)	0.314	0.457	0.398	0.272	0.469	0.423

Note: This table presents the robustness findings, controlling for country-level factors, for the impact of ESG activity on bank lending in crisis times. We use a sample of 83 listed banks from 20 European countries and yearly data for 2002–2020. We implement the two-step system GMM dynamic panel data estimation techniques. The first lags of explanatory variables are used to mitigate any potential reverse causality. Country-fixed effects are used in all models. The dependent variable is the annual growth rate of total loans, *LOANGRW*, in all models. Columns 1–6 use baseline estimations and control for the following country-level factors in order: *ESG MANDATORY DISCLOSURE*, *CDS SPREAD*, *PARIS*, *INVESTOR PROTECTION*, *ADRI*, *ASDI*. Variable definitions can be found in Table 1. Windmeijer corrected standard errors are used when clustering the error terms and are given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table A.5**  
Robustness Checks- Alternative Crisis Variables.

	(1)	(2)	(3)	(4)
			<i>MOST AFFECTED COUNTRIES</i> = 1	<i>MOST AFFECTED COUNTRIES</i> = 0
<i>ESG</i>	-0.006 (0.08)	-0.002 (0.03)	-0.087 (0.14)	0.124*** (0.02)
<i>BANKING CRISIS</i>	-27.950*** (5.71)			
<i>ESG *BANKING CRISIS</i>	0.482*** (0.11)			
<i>MOST AFFECTED COUNTRIES</i>		-1.321 (0.86)		
<i>CRISIS</i>		-12.677*** (2.85)	-24.278 (18.84)	-14.445*** (2.07)
<i>ESG * CRISIS</i>		0.173*** (0.05)	0.298 (0.30)	0.226*** (0.05)
Constant	194.879*** (34.88)	38.289*** (5.92)	60.653 (60.35)	57.981*** (12.74)
Country FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Number of observations	397	774	304	470
Number of banks	48	75	24	55
Number of instruments	41	43	20	51
Hansen p-value	0.572	0.189	1.000	0.438
AR (2)	0.407	0.402	0.174	0.438

Note: This table presents robustness findings, using alternative crisis variable definitions, for the impact of ESG activity on bank lending in crisis times. We use a sample of 83 listed banks from 20 European countries and yearly data for 2002–2020. We implement the two-step system GMM dynamic panel data estimation techniques. The first lags of explanatory variables are used to mitigate any potential reverse causality. Country-fixed effects are used in all models. The dependent variable is the annual growth rate of total loans, *LOANGRW*, in all models. *BANKING CRISIS* is an indicator variable, taking a value of 1 if there is a banking crisis in that year in the corresponding country. *MOST AFFECTED COUNTRIES* is an indicator variable that equals 1 for the most affected European countries from the financial crisis, which include Greece, Spain, Ireland, Cyprus, Portugal, and Italy. Variable definitions can be found in Table 1. Windmeijer corrected standard errors are used when clustering the error terms and are given in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

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