Banks' environmental policies and banks' financial stability

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A B S T R A C T

We study whether environmental engagement of banks mitigates the effects of natural disasters and climate-change related events on financial stability. Employing an extensive global dataset with quarterly data (2003–2019; 5,317 observations), our analysis reveals that environmental innovation financing, product responsibility, and resource reduction policies are able to curtail the repercussions on stability of economic costs due to environmental events. We also find that the lending function of banks is a relevant mediating channel for this relationship. Since borrowers' vulnerability to climate issues may be reflected in non-performing loans, banks' environmental engagement provides protection against future related credit losses. Moreover, by capitalizing on global disasters as quasi-natural experiments, we provide empirical evidence confirming that a stronger environmental engagement of banks enhances their post-event financial resilience. Taken together, our results convey several key implications: i) bank executives can improve financial stability by embracing environmental policies, ii) stronger regulatory actions towards environmental sensitivity in the banking sector is supported, and iii) environmentally engaged banking systems can mitigate the economic costs associated with climate change and environmental disasters.

1. Introduction

Climate change, with its multifaceted societal impacts, has the potential to undermine financial stability. Although the existing literature on this relationship is somewhat limited, it suggests that climate change emerged as a recent prominent source of risk, affecting both asset price volatility and stability (Monasterolo and Raberto, 2017). The influence of climate change on financial stability manifests in two ways (Battiston et al., 2017): physical risk (loss of assets due to environmental shocks or costs), and transition risk (negative influence on environmentally exposed industries from strengthened regulations). In the spirit of Chiaramonte et al. (2022), we empirically ascertain whether the environmental engagement undertaken by banks has the capacity to diminish the physical risk exposure of their respective countries, proxied by associated mortality/morbidity welfare costs, while achieving higher financial stability. We also assess whether the lending function of banks, proxied by non-performing loans, represents a mediating economic channel.

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We build an unbalanced dataset composed of 5,317 bank-quarter observations from 2003 to 2019, with a worldwide scope (Africa, Asia, Europe, Latin America, North America, and Oceania). In line with the literature (Liang and Renneboog, 2017), we proxy the environmental engagement of banks through different environmental scores and policy measures, as provided by Thomson Reuters Refinitiv. As most providers of Environmental scores, these are less likely to provide measures of physical risk exposures: we use them as proxies for engagement, while combining this information with country-wide (mortality/morbidity welfare costs) and bank-specific (non-performing loans) proxies of physical risks. In particular, for non-performing loans, we see if besides being an expression of climate risks (association with welfare costs), they are also consistently reduced by enhanced environmental engagement, while worsening the general stability of banks.

Our empirical strategy involves two approaches: i) regression analysis with time and bank fixed effects exploring the nexus between environmental engagement, climate change costs, and financial stability; ii) a DID framework built around climate-related natural disasters, to evaluate marginal responses between highly and less engaged banks. Moreover, we successfully confirm our findings through a series of robustness tests, including changes in model specifications, endogeneity issues, and alternative measures for key variables.

The empirical approach of this paper focuses on stability measured at the bank-level, while countries provide one leading target variable (i.e., climate welfare costs), controls (f.i. inflation), and a reference for creating regional subsamples affected by natural catastrophes, depending on the specific analysis that we implement.

Our results show that highly environmentally engaged banks experience a lower probability of default when country-level climate costs increase. We find that the main drivers are the environmental score, the environmental innovation score, the environmental product responsibility policy, and the resource reduction policy adoption. This relationship is stronger immediately after natural disasters (exogenous shocks), suggesting a potential causal relationship between banking environmental policies and financial stability. Additionally, we find that a mediating role is played by lower non-performing loans, as climate change costs increase.

Our contribution is threefold. First, we empirically show that more environmentally engaged banks have greater stability, especially in the aftermath of disasters. Second, we find that the physical risk of climate change, proxied by non-performing loans, is reduced by environmental engagement. Lastly, unlike previous studies, we test our hypotheses on an extended high-frequency global data set, accounting explicitly for the climate-related engagement of banks.

The remainder of this paper is structured as follows. In Section 2 we review the literature and develop our hypotheses. Section 3 describes our empirical strategy and the sample selection procedure. Section 4 describes baseline findings, while Section 5 presents robustness tests. Finally, Section 6 concludes.

2. Background and hypotheses development

The literature on the relationship between climate change and financial markets has increasingly attracted researchers, policymakers, and regulators. Climate change costs hamper labor productivity (Dell et al., 2012), impact the pricing of carbon-based assets (Mercure et al., 2018; Ahonen et al., 2022), and enhance the risk of contagion between financial institutions and firms exposed to stranded assets (Battiston et al., 2017; Corbet, Goodell, and Günay, 2020). We consider that financial markets and institutions should account for all causes of borrowers' insolvency.

Two main mechanisms explain how financial markets are affected by climate change: i) 'transition risk,' as losses occur after regulatory changes affect the asset pricing of non-compliant industries; and ii) 'physical risk,' as losses arise directly from climate change costs and damages. From the transition risk perspective, Dunz et al. (2021) introduces a stock-flow model to determine the effect of regulatory policy actions, such as carbon taxes and green supporting factors, on the transmission of risks to the economy through the bank credit market. If policies are introduced rapidly, cascading effects may occur on the credit supply chain: authors conclude that effective policies should be supported by redistribution aiming at reducing the negative effects on non-performing loans (NPL) and household income. Similarly, Stiglitz et al. (2017) argue that carbon pricing and taxation will be the larger, the later they are introduced, with growing impacts for welfare and financial stability. The banking sector, despite recognizing the implications of climate change on their performance, shows an overall limited cross-country effort in increasing their engagement (Caby et al., 2022).

Few studies investigate the impact of the physical risk component of climate change in financial institutions. One of the main reasons depends on most providers of firm-level exposures building their metrics more closely to the transition risk (preferences of consumers and investors, public policies and regulations, etc.). However, these measures are able to frame the engagement of firms and to compare their non-financial performance on an international basis. At the same time, taken alone, such scores are unable to measure the actual physical risk exposure, a limitation that we try to overcome in this paper.

Diez et al. (2016) introduce the concept of 'climate value at risk', finding that it accounts for 1.8 % along a business-as-usual emissions path in 2016, which translates to a global amount of $2.5 trillion. Additionally, they find that the highest amount of this risk is in the tale of the distribution (99th percentile). Therefore, policy interventions aimed at reducing greenhouse gas emissions to decrease global warming may affect climate value at risk by an average 0.6 percentage points. Similarly, Dafermos et al. (2018) demonstrate that climate change costs are strongly correlated to leverage and the stability of financial markets. Consequently, climate change may negatively and significantly affect GDP growth by the end of the century.

Few contributions focus on climate change costs to banks and economic growth, with even fewer adopting quasi-natural experiments that exploit the informative potential of exogenous natural disasters. Bos et al. (2022) investigate banks' strategical adjustments to their asset structure after natural disasters, and document that US headquartered banks tend to increase real estate lending and reduce holdings of government bonds. Moreover, they conclude that the higher the risk of natural disasters, the lower the ability of banks to finance local firms.

A few papers provide interesting insight on the relationship between banking and natural disasters. Klomp (2014), examining the period 1997–2010, finds that natural disasters are associated with a reduction in banks' distance to default, mostly linked to the size and nature of the disaster, as well as the degree of economic development (including regulation and supervision). Schüwer et al. (2019) utilize the exogenous event of Hurricane Katrina (2005) to assess reactions to the shock in the banking system, finding a positive association with county-level economic growth in the aftermath of disasters. Noth and Schüwer (2023) investigate how US natural disasters negatively influence the stability of banks, using county-level data. However, despite investigating the bank stability-natural disaster relationship, studies are not providing up-to-date data and do not consider the environmental engagement of banks. Further, they typically focus on narrow geographical scopes.

According to Duqi et al. (2021), banking systems play a pivotal role in economic recovery following a natural disaster. Chiaramonte et al. (2022) find a positive relationship between sustainability, proxied by environmental, social, and governance (ESG) scores, and European banks' stability during financial shocks, including a meaningful discussion on the related causality link. We differentiate from their contribution in several ways: 1) we focus on non-financial shocks; 2) we analyze a global dataset; 3) we consider a greater frequency of data; 4) we provide a deeper insight on the environmental dimension and proxies for climate change costs; 5) we test the mediating role of non-performing loans.

To what extent climate change costs and natural disasters affect the stability of banks, and how they may reduce this exposure, is still unclear. If their environmental engagement plays a role in influencing financial stability, how do they react to exogenous shocks, and what is the channel supporting this nexus represent our main research questions.

Consistently with the literature, we expect banks that are more engaged in environmental matters to experience a lower impact from increasing physical risks. Transition risks may be considered at the country-level with metrics that combine wider dimensions, such as associated mortality/morbidity welfare costs. Physical risks also impact bank-specific dimensions, as reflected by non-performing loans. Additionally, financial markets' perception of firm-level resilience, such as the probability of default, are impacted in response to expected levels of volatility and losses.

Lastly, these relationships could be enhanced in the aftermath of environmental disaster, when related new information is employed by market players while evaluating firms, financial systems, and country responses. This additional analysis is designed to check the robustness of the hypothesized relationship, and to facilitate inference about potential causality links between environmental engagement and financial stability.

Overall, we develop two hypotheses to be tested. We expect that banks that are more environmentally engaged will have lower exposure to climate change costs and better financial stability. Moreover, we also expect that the main channel explaining this nexus can be found in non-performing loans. However, confirming this association does not in itself prove a causal relationship. Therefore, we investigate a quasi-natural experimental setting in a DID framework to investigate bank-level reactions to exogenous natural shocks. Additionally, as results of a DID framework are vulnerable to a lack-of-sample bias, endogeneity, reverse causality, and omitted variables, we complement our analysis with a wide range of meaningful robustness checks.

In summary, our two main hypotheses are the following:

H1. Environmental engagement of banks (transition risk) reduces their exposure to climate change costs (physical risk) at the country level, and positively affects their financial stability through the non-performing loans economic channel (physical risk).

H2. Banks with higher environmental engagement experience a stronger financial stability in the aftermath of natural disasters.

3. Data and methodology

3.1. Empirical strategy

To address the impact of climate change and natural disasters on bank stability, contingent on the level of environmental engagement, we employ a two-step empirical strategy. First, we evaluate if the increasing country-level costs of climate change affect a bank's financial stability, as well as whether a moderating role is played by each bank's environmental engagement. We implement the following OLS regression:

$$PD_{i,t} = c + \beta_1 ClimateChange^{*}ENV_{i,t-1} + \beta_2 ENV_{i,t-1} + \beta_3 ClimateChange_{i,t-1} + \boldsymbol{\gamma}'\boldsymbol{X}_{i,t-1} + Bank_i + Time_t + \varepsilon_{i,t} \tag{1}$$

where the 3-months probability of default (PD) is the proxy for stability of bank i at quarter t. The PD represents a market-based indicator (provided by Bloomberg Professional Services, as opposed to accounting-based metrics such as the Z-Score), log-transformed to reduce the potential bias arising from outliers and non-linearities (Eichler and Sobański, 2016). The PD reflects the solvency and exposure to risks of a bank and is calculated by the provider as a point-in-time (PIT), credit default swap based probability of default (for further reference, see Bondioli et al., 2021). The PD, as a proxy for bank stability, grants an up-to-date current estimate on how credit risk may also reflect climate change losses: market participants may appraise a positive impact on lending of environmental engagement in terms of reduced loan losses, in general terms or as a result of exogenous shocks (Lee et al., 2022).

Regarding our primary variable of interest, following Chiaramonte et al. (2022), we measure each bank's environmental engagement using in turn the environmental component of ESG scores and its constituents (later, for robustness purposes, also with alternative metrics). These variables are collected from Thomson Reuters Refinitiv. This provider allows a comprehensive breakdown of all metrics aggregated into ESG scores. These include the scores for each pillar and the scores for each of the 10 subpillars.[1]

We interact each target variable with the country-level measure of *ClimateChange*. This variable is proxied by welfare costs arising from exposure to climate change risks due to higher temperatures, obtained from GBD (2019), and calculated adapting the methodology of Roy and Braathen (2017). The GBD is "the most comprehensive epidemiological study to date" with data currently available from 1990 to 2019 for 204 countries and 87 risk factors.[2] Our dataset on these metrics is provided by *OECD.stat*. A further advantage of this data is that it includes welfare costs related to weather.

Our empirical approach allows us to explore if banks environmental engagement acts as a risk mitigation tool towards exposure to climate change costs. Additionally, we include a list of bank controls that are usually correlated with bank stability: size, capitalization, credit risk, efficiency, profitability, liquidity, income diversification, as well as bank and quarter fixed effects terms (*Bank*, *Time*), clustering the standard errors at the bank level.

Our second step aims at exploring if the engagement-stability relationship exists when exogenous natural disasters occur. Therefore, we implement a differences-in-differences (DID) regression setting, built around a set of natural disasters. These include the 2011 Fukushima disaster (Asia); the 2011 Hurricane Irene (North America); the 2017 Hurricane Ophelia (Europe); and the 2012 Bopha/Pablo typhoon (Oceania).

The rationale behind the selection of these events is that they currently represent the most impacting in terms of associated costs and deaths worldwide, while at the same time differentiating between four major geographical areas. Tropical cyclones alone affect a large number of countries (89 countries) and people (from 1 billion in 1975 up to 1.6 billion in 2015[3]). We consider that selected events represent an ideal setting for testing if banks environmental engagement mitigates the impact on their stability from exposure to exogenous shocks. The choice of the Fukushima disaster stands out from this selection by being not directly the consequence of a climate change related effect. On one side, weather-related catastrophes are expected to increase globally due to climate change but are not entirely caused by it. On the other hand, the Fukushima disaster remains related to the climatic implications of energy production and may also have indirectly changed market perceptions on climate change. Therefore, we implement the following empirical specification:

$$PD_{i,t} = c + \beta_1 SHOCK{*}TREATED_{i,t} + \beta_2 TREATED_{i,t} + \beta_3 SHOCK_{i,t} + \boldsymbol{\gamma}' \boldsymbol{X}_{i,t-1} + Bank_i + \varepsilon_{i,t}$$

where *PD* is the 3-months probability of default, the dummy *SHOCK* represents the outbreak of the selected natural disaster at time *t*, taking the value of 1 for three post-shock quarters (designed to avoid that outcomes are only due to the immediate reaction to the event itself with limited effects on climate change welfare costs) and 0 otherwise. The dummy *TREATED* assumes the value of 1 for banks with above average values for the target environmental score in the quarter before the natural disaster and 0 otherwise. The variable *SHOCK*TREATED* is the interaction representing our target variable, capturing the marginal effect of banks being highly environmentally engaged on their respective stability after a natural disaster. As in Equation (1), we include a set of bank-level controls, bank fixed effects, and error clustering at the bank level,[4] while confirming the parallel trend assumption (Huang et al., 2022).

3.2. Sample

To empirically investigate our hypotheses, we select all banks as defined by the Global Industry Classification Standards (GICS), with non-missing values for target environmental scores available in Thomson Reuters Refinitiv, from 2003 to 2019 (earliest and latest data available). We do not limit our sample geographically, and hence obtain observations in all continents, allowing us to explore the cross-country variation of environmental engagement of banks. The final sample consist of an unbalanced panel of 266 banks (5,317 obs.) distributed as follows: 18 % in Asia, 39 % in Europe, 4 % in Oceania, 4 % in South America and 34 % in North America. Appendix A.3 offers a summary of our sample by country and region.

3.3. Environmental engagement and climate change measures

To measure banks' environmental engagement we follow Liang and Renneboog (2017), proxying this dimension through the 'E' pillar of ESG scores, as well as its constituents. Thomson Reuters Refinitiv adopts a methodology aimed at showing how firms perform relative to their peers: all scores are industry-weighted and thus capture banking-specific characteristics.

As constituents of the environmental pillar, we follow Chiaramonte et al. (2022) and use scores for 'environmental', environmental innovation', 'environmentally responsible production policy,' and 'resource reduction policy financing'. The first two scores range from 0 (worst) to 100 (best), while the latter two take values of 1 for engaged banks and 0 otherwise. We consider that the 'E' score is a consistent and precise way to account for the intensity of banks' environmental engagement. This engagement includes the use of

[1] For more information about Thomson Reuters Refinitiv methodology as of 2022, visit https://www.refinitiv.com.

[2] For further information see The Lancet, Global Burden of Disease, https://www.thelancet.com/gbd.

[3] See European Commission report: https://knowledge4policy.ec.europa.eu/foresight/topic/climate-change-environmental-degradation/high-impact-events-natural-disasters_en.

[4] Evidence is similar by clustering standard errors at country levels. Results are available upon requests.

resources through green investments, emission targeting through green asset allocations, and innovative products such as “green” loans. Nevertheless, we also consider additional avenues of environmentalism by controlling for whether or not a bank adopts a carbon policy or the Equator Principles Initiative, using Bloomberg’s environmental scores.

To avoid a potential source of bias, we also use a set of additional variables accounting for the adoption of specific environmental policies, based on raw self-reported firm information (such as financial statements and company news).

We proxy country-level climate change costs with data on mortality/morbidity and welfare costs from exposure to environment-related risks provided by the OECD.stat database (dataset code: EXP_MORSC). This dataset has been increasingly used in recent empirical works (e.g., Roy and Braathen, 2017) and provides comparable metrics on welfare costs related to climate change, in expenses scaled by the gross domestic product (in US dollars).

Additionally, as a robustness check, we alternatively proxy climate change as the abnormal surface temperature, with data provided by *OECD Green Growth* (dataset code: GREEN_GROWTH). Table 1 shows the selected variables and their sources.

3.4. Descriptive statistics

Table 2 shows the descriptive statistics of our variables: dependent (PD), independent (controls) and target (*Env, Env_innov, Res_red, Env_prod, Climate_costs*). The quarterly probability of default (PD) ranges between 0.0001 (min) to 0.10 (max), *Env* and *Env_innov* scores are between 0 and 0.98 and 0.96 (respectively), with an average value of 0.40 and 0.28, respectively. This suggests that banking sector’s engagement with environmental policies is widely variable, and “timid” (Caby et al., 2022).

Similarly, banks adopting financing policies aimed at resource use reduction (*Res_red*) and environmental responsible products (*Env_prod*) are 42 % and 57 % of the final sample, respectively. Costs related to climate change (*Climate_costs*) amount to an average of 6 % of the country GDP, and range between 0.1 % (lowest) to 54 % (most exposed). Concerning bank-level control variables, descriptive statistics are consistent with the related literature (Chiaramonte et al., 2022).

4. Results

4.1. Multivariate results

Table 3 shows the results of our baseline OLS regression with bank and time fixed effects, where the dependent variable is the quarterly probability of default (*PD*). As target variables, we employ the environmental score (*Env*), as well as its constituents: environmental innovation (*Env_inn*), resource reduction policy (*Res_red*), environmental responsible products policy (*Env_prod*). As explained in the previous section, we interact them with climate change costs (*Climate_costs*).

Results show that banks’ environmental scores are always negatively and statistically significantly correlated to their probability of default, but only when costs related to climate change increase. These initial results are consistent with our H1: banks’ environmental engagement is associated with a reduction in the impact of climate change on banks’ stability. Regarding the economic significance, we estimate that an increase of one standard deviation of the environmental score, the environmental innovation, the resource reduction policy or the environmental responsible products policy is associated with a decrease of 1, 0.2, 2.4, and 3.4 % in PD, respectively.

Looking at the coefficient of *Climate_costs*, we find that it is positively correlated to *PD*, supporting the economic and financial detrimental impact of a country’s exposure to climate change and the related welfare costs. However, this result is not statistically significant when the target variable is represented by the overall ENV score. We argue that this effect may be due to the broad subset of constituents that participate in forming the final score, whereas our main purpose is to disentangle the relationship with the specific exposure to climate change. As with previous studies (Chiaramonte, et al., 2022; Lins et al., 2017) environmental activities are statistically significant only when climate costs increase, worsening market conditions. This is consistent with a stakeholder theory framework, as well as the moral capital assumptions: the pricing of environmental engagement, during adverse market conditions and including those catalyzed by climate change, impacts banks’ stability.

These multivariate results support the concern that regulators, investors, and banks should consider climate change costs and policies as a material threat to stability. The economic magnitude of climate change impact strongly depends on banks’ engagement in environmental and climate-aligned practices and policies (CISL, 2015; Trucost, 2018).[5]

Regarding control variables, our results are consistent with papers in closely related fields of research. Return on assets (*Roa*) and liquidity (*Liq*) are negatively and significantly correlated with bank stability (*PD*). More profits and greater liquidity are expected to be associated with a reduction in banks’ overall risks. Size is weakly statistically significant in three out of four specifications. Larger banks are associated with a greater probability of default. Additionally, we find that asset quality (*Llr_gl*) is strongly significant. The need to reserve greater amounts for credit losses is perceived negatively by markets in terms of banks’ stability. Finally, we find no statistically significant associations with revenue diversification (*Div*), cost-income ratios (*Cir*), or leverage (*Eta*).

4.2. Evidence from natural disasters

Our baseline models evidence a robust average negative association between banks’ environmental engagement and default

[5] In unreported additional tests, we address the issue of lags by testing if our baseline results hold when increasing them to two or three quarters. Findings, available upon request, remain consistent (i.e., the significant interaction between climate costs and environmental variables).

Table 1
Variable definitions. This table describes our variables, their definitions, and data sources.

Variable	Definition	Source
PD	Natural logarithm of the probability of default (quarterly data)	Bloomberg and authors' calculation
Env	Environmental score is an overall score measuring the adoption of environmental practices.	Thomson Reuters Refinitiv
Env_inn	Environmental innovation score is an overall score measuring the engagement in environmental innovation financing practices.	Thomson Reuters Refinitiv
Prod_resp	Environmental product responsibility policy is a dummy variable taking value of 1 for banks financing and investing on environmental responsible products and 0 otherwise.	Thomson Reuters Refinitiv
Res_red	Resource reduction policy is a dummy variable taking value of 1 for banks financing resource reduction practices and 0 otherwise.	Thomson Reuters Refinitiv
Climate_costs	A measure of the welfare costs of climate change (high temperature) scaled by country GDP, in US dollars.	OECD.stat, EXP_MORSC dataset
Abn_temp	A measure of the country-level abnormal surface temperature compared to the mean value of the 1950–1985 period.	OECD.stat, GREEN_GROWTH dataset
Size	Natural log of total assets.	Thomson Reuters Refinitiv and authors' calculation
Eta	Equity to total assets.	Thomson Reuters Refinitiv and authors' calculation
Llr_gl	Loan loss reserves to gross loans.	Thomson Reuters Refinitiv and authors' calculation
Roa	Return on assets: net profit on total assets.	Thomson Reuters Refinitiv and authors' calculation
Liq	Cash holdings to total assets.	Thomson Reuters Refinitiv and authors' calculation
Div	Non-interest income to net operating revenues.	Thomson Reuters Refinitiv and authors' calculation
Cir	Cost-income ratio.	Thomson Reuters Refinitiv and authors' calculation

Table 2
Summary statistics. This table reports the summary statistics of the variables included in Equation (1) for the whole sample period (2003–2019). Variable definitions are provided in Table 1. The correlation matrix across these variables is reported in Table A.1 in the Appendix.

	Mean	S.D.	Min	Max
PD	0.0010	0.0050	0.0001	0.1060
Env	0.4047	0.3252	0	0.9623
Env_inn	0.2850	0.3417	0	0.9871
Prod_resp	0.4256	0.4944	0	1
Res_red	0.5706	0.4950	0	1
Climate_costs	0.0633	0.0919	0.0010	0.5476
Abn_temp	1.167	0.5401	-0.2631	2.717
Size	19.090	3.0481	1.348	26.541
Roa	0.0091	0.0083	-0.0209	0.0656
Llr_gl	0.0065	0.0098	-0.0127	0.1003
Liq	0.0459	0.0531	0.0002	0.7819
Div	0.2798	0.1298	0.0203	0.6629
Cir	0.4115	0.3410	0.0103	0.7010
Eta	0.0824	0.0338	0.0001	0.2566

probabilities, especially when climate change costs increase. However, we also seek to explore if this effect exists when exogenous natural disasters occur. To address this question, we evaluate the marginal effect of adopting environmental policies on stability by running a set of quasi-natural experiments built around environmental disasters, testing if more sustainable banks perform differently from others in terms of associated default probabilities.

We select four regional severe natural disasters (Asia, North America, Oceania, and Europe), for January 2003–December 2019.[6] As in Liang and Renneboog (2017), we select the 2011 Fukushima disaster for the Asian region, the 2011 Hurricane Irene for North America, the 2012 Bopha/Pablo typhoon for Oceania, and the 2017 Hurricane Ophelia for Europe. While hurricanes and typhoons are more clearly associated to climate change, the same could not be said for an earthquake resulting in a nuclear incident. However, we include the Fukushima disaster since we expect that natural disasters influence markets by providing additional information on potential threats posed by large-scale climate-related events.

Additionally, while nuclear power plays a role in the energy mix of a number of countries, including for carbon-neutrality reasons, the Fukushima incident caused a major increase in the Japanese consumption of fossil fuels as a result of the shutdown of nuclear

[6] We also tested other disasters with lower cross-country impact. Results are qualitatively similar and available upon request.

Table 3
Baseline results. This table reports the estimates of the OLS regression for 2003–2019. The dependent variable is the probability of default (PD) which measures a bank's stability. The variables of interest are: the *Env* score - column (I); the *Env_inn* score, *Prod_Res* and *Res_Red* - columns (II), (III), and (IV), respectively. Each target variable is interacted with *Climate_costs* (which measures the country-level costs of climate change). Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one period with respect to the dependent variable. The control variables based on accounting data (*Size*, *Roa*, *Liq*, *Llr_gl*, *Eta*, *Div, Cir*) are winsorized at the 1% of each tail. Bank and time fixed-effects (FE) are included in all specifications. Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Variables	PD (I)	(II)	(III)	(IV)
Climate_costs*Env (-1)	−0.00143*			
	(0.000770)			
Env (-1)	−0.0116			
	(0.00712)			
Climate_costs*Env_inn (-1)		−0.000885**		
		(0.000378)		
Env_inn (-1)		−0.00113		
		(0.00497)		
Climate_costs*Prod_res (-1)			−0.0568***	
			(0.0210)	
Prod_res (-1)			0.00313	
			(0.00333)	
Climate_costs*Res_red				−0.0701**
				(0.0295)
Res_red (-1)				−0.00132
				(0.00315)
Climate_costs	0.0720	0.104**	0.110**	0.132**
	(0.0503)	(0.0524)	(0.0508)	(0.0540)
Size (-1)	0.00959*	0.00900	0.00949*	0.00998*
	(0.00567)	(0.00584)	(0.00570)	(0.00580)
Roa (-1)	−0.711***	−0.720***	−0.712***	−0.719***
	(0.188)	(0.186)	(0.185)	(0.186)
Llr_gl (-1)	0.766***	0.772***	0.751***	0.753***
	(0.177)	(0.177)	(0.180)	(0.183)
Liq (-1)	−0.0943**	−0.0860**	−0.0847**	−0.0793*
	(0.0401)	(0.0406)	(0.0405)	(0.0403)
Div (-1)	−0.0178	−0.0160	−0.0196	−0.0163
	(0.0215)	(0.0215)	(0.0217)	(0.0217)
Cir (-1)	0.00165	0.00162	0.00133	0.00147
	(0.00299)	(0.00301)	(0.00295)	(0.00297)
Eta (-1)	−0.0247	−0.0254	−0.0242	−0.0270
	(0.0773)	(0.0777)	(0.0764)	(0.0786)
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes
Obs.	5,317	5,317	5,317	5,317
R-squared	0.752	0.751	0.751	0.751

plants, with concomitant increases in climate change implications. Other studies examine the association between the Fukushima incident and climate change risks (Bird et al., 2014; Poortinga et al., 2013), as well as use this event as a quasi-natural experiment to address market reactions to climate change (Lei and Shcherbaka, 2015).

Overall, we evidence a negative association between default probabilities and environmental engagement of banks, in the aftermath of an exogenous natural disaster (Table 4). Moreover, we estimate that the reduction in default probabilities for highly environmentally engaged banks ranges between 8 % and 29 %. We obtain these marginal differences dividing the coefficient of the Treated*Shock variable of each of the four disasters (Table 4, Panel A) and the mean value of the sampled probability of default (0.001). More specifically, the reduction in default probabilities that we measure is around 10 % for the Fukushima disaster, 8 % for the US Irene hurricane, 2.4 % for the Bopha/Pablo typhoon, and 29 % for the EU Ophelia hurricane.

Finally, Fig. 1 shows the results of the parallel trend assumptions, confirming the validity of the difference-in-difference regressions.

4.2.1. Fukushima

The 2011 Fukushima nuclear disaster was the most severe nuclear accident of the past decades, being classified as '7′ (highest) on the International Nuclear Event Scale (INES). Following the earthquake, a tsunami hit the Fukushima Daiichi Nuclear Power Plant.

Table 4

Evidence from natural disasters. This table shows the results of four differences-in-differences (DID) regressions aimed at verifying the causal relationship between natural disasters, environmental performance, and bank stability. Panel A shows the parallel trend assumption, whereas Panel B provides the DID results for each shock: Column (I) for the 2011 Asian Fukushima disaster; Column (II) for the 2011 US Irene hurricane; Column (III) for the 2012 Oceania Bopha/Pablo typhoon; Column (IV) the 2017 European Ophelia hurricane. The dependent variable is the PD. The target variables are: *Treated*, equal to 1 for banks with the *Env* score above the mean value and 0 otherwise; *Shock*, which takes the value of 1 since the quarter of the natural disaster and 0 otherwise; and their interaction (*Treated* Shock)*. All models include control variables as in Eq. (1). Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one year with respect to the dependent variable. Models include bank fixed effects (FE). Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Panel A: Parallel trend assumption

t-test Natural disaster	Before the natural disaster Treated (T)	Controls (C)	Diff (C-T)	P-value
2011 Fukushima Disaster	0.0001	0.0004	0.0003	0.10
2011 US Hurricane Irene	0.0001	0.0010	0.0009	0.37
2012 Oceania Typhoon Bopha/Pablo	0.0010	0.0010	0	0.45
2017 EU Hurricane Ophelia	0.0140	0.0230	0.0090	0.42

Panel B: DID results

	PD 2011 Asian Fukushima Disaster	2011 US Irene Hurricane	2012 Oceania Bopha/Pablo Typhoon	2017 European Ophelia Hurricane
Variables	(I)	(II)	(III)	(IV)
Treated*Shock	−0.0104**	−0.00838***	−0.0247*	−0.0294***
	(0.00424)	(0.00185)	(0.0103)	(0.00315)
Treated	0.00600	−0.0157	0.0117	0.00894
	(0.0105)	(0.0315)	(0.00881)	(0.00985)
Shock	0.0127***	0.0123***	−0.0143	0.0170***
	(0.00400)	(0.00244)	(0.0110)	(0.00359)
Controls (-1)	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes
Obs.	715	1,234	114	511
R-squared	0.692	0.737	0.844	0.799

Subsequently, the Japanese government evacuated a 20-km radius zone. The economic loss of this event was estimated to be about 360 billion US dollars with the destruction of 138,000 buildings.[7] Additionally, the 2011 Fukushima disaster led the Japanese government to substitute the gap in the energy supply following the shutdown of nuclear plants with imports of fossil fuels, with concomitant increasing costs, and instability of supply. Therefore, this event represents a useful exogenous shock to assess if banks with higher (lower) environmental ratings performed better (worse) in terms of stability after a disaster.

We split our sample between banks with higher (treated, values above the sample average) and lower (controls, with values below the sample average) ENV scores, testing if any statistically significant difference exists between the two groups. Examining Table 4, Panel B, we see that the coefficient of the interaction term (*Treated*Shock*) is significant and negative, confirming an association between environmental engagement of banks and financial stability after the 2011 Fukushima disaster, consistently with our second hypothesis (H2).

4.2.2. The 2011 Hurricane Irene in US

Hurricane Irene was a massive tropical cyclone impacting the Caribbean and the East Coast of the United States at the end of August 2011. The Hurricane originated from an Atlantic tropical storm that grew quickly to achieve a rank of ‘3′ (out of ‘5′) on the Saffir-Simpson scale. Irene put more than 65 million US citizens at risk, as well as impacting a variety of industries including utilities, transportation facilities, ports, industries, oil refineries, and nuclear power plants.[8] Consequently, the impact spread rapidly to the real economy and the financial industry. Again, this natural disaster represents a useful framework to explore the hypothesized marginal superior stability of highly environmentally engaged banks in a DID setting.

We split our sample between banks with higher (treated) and lower (controls) ENV scores, testing if any statistically significant difference exists between the two groups. Table 4 (Panel B) supports our H2: treated banks express lower default probabilities in the aftermath of the shock.

4.2.3. Bopha/Pablo typhoon

Typhoon Bopha/Pablo is one of the strongest storms ever to have affected the Southern Philippines, being ranked ‘5′ (highest) on

[7] See, for instance, Brookings Institution: https://www.brookings.edu/blog/up-front/2013/03/11/earthquake-tsunami-meltdown-the-triple-disasters-impact-on-japan-impact-on-the-world/.

[8] Reuters, August 25, 2011: US East Coast in Irene’s path, scrambles to prepare. https://www.reuters.com/article/uk-storm-irene-idUKTRE77M1YR20110825.

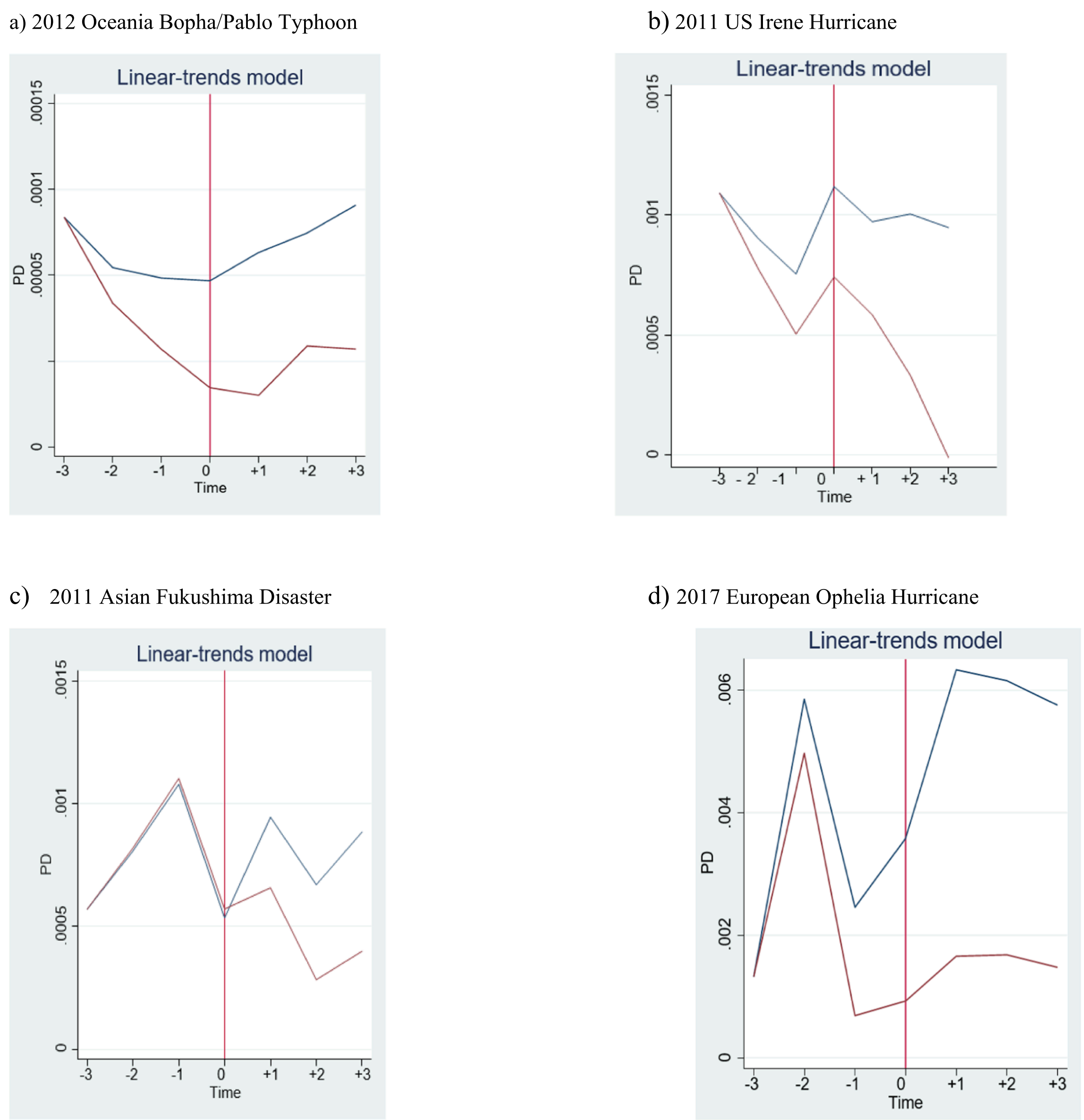

Fig. 1. Parallel trend results. This figure shows the result of graphical parallel trend assumptions for selected regional shocks. Specifically, it shows the different trend of probability of default (PD) for treated (red line) vs control (blue line) banks. Horizontal axis is years before or after specific event year. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the Saffir-Simpson scale. In the case of this storm, the impact on the regional economy was substantial, including the financial industry, with both direct and indirect effects on banks. Therefore, the use of this exogenous event to investigate our hypotheses is appropriate.

We split once more our sample between banks with higher (treated) and lower (controls) ENV scores, finding a statistically significant difference between the two groups. As reported in Table 4, Panel B, analysis of this natural disaster supports our H2.

4.2.4. Hurricane Ophelia

The last selected shock involved Europe in 2017. Hurricane Ophelia was ranked third (out of five) in the Saffir-Simpson scale. Originating in the Eastern Atlantic, it rapidly became the farthest-east major hurricane observed in the satellite era.[9] The fierce winds severely affected Ireland, the United Kingdom, Spain, Portugal, and France, causing property damage, deaths, injuries, and economic costs.

[9] National Hurricane Center, 2018, Tropical Cyclone Report, Hurricane Ophelia (AL172017). https://www.nhc.noaa.gov/data/tcr/AL172017_Ophelia.pdf.

To address our research question, we employ again a DID setting to this exogenous shock to explore if a marginal negative relationship exists between default probabilities and higher environmental engagement of banks. We once more split our sample between banks with higher (treated) and lower (controls) ENV scores, testing if any statistically significant difference exists between the two groups. Table 4 (Panel B) confirms that treated banks experience lower default probabilities in the aftermath of the natural disaster.

5. Additional tests and robustness checks

5.1. Economic channel test: Non-performing loans

One of the drivers of the sustainability/stability relationship of banks can be found within the moral capital – risk mitigation mechanism alleviating market risk exposures of highly engaged firms (Bouslah et al., 2018; Chiaramonte et al., 2022). Since in this paper we explore if environmental engagement of banks lowers their default probability while mitigating the welfare costs of climate change, we assess if other economic channels exist to support the environmental-stability relationship.

According to Lamperti et al. (2021), during economic downturns green policies of banks (e.g., green credit and financing) reduce the exposure to non-performing loans, and so soften adverse impacts on financial performance. Therefore, we evaluate if the ratio between non-performing loans and gross loans (NPL ratio) represents a valid economic channel in explaining our sustainability-stability target relationship.

Consistently with Cheung (2016), we assess if our target variables are correlated with the NPL ratio, and if the statistical significance holds when including *Npl* in our Equation (1). Table 5 reports the results of this test. The NPL ratio is the dependent variable in different specifications (summarized in Columns I, II, III, IV), whereas the augmented baseline model is reported in columns V, VI, VII, and VIII.

We find that measures of bank environmental practices (*Env_score, Env_inn, Prod_res and Res_red*) are always negatively significantly correlated with the NPL ratio when interacted with climate costs, consistent with the theoretical assumptions proposed by Lamperti et al. (2021).

Moreover, we document that the sustainability-stability relationship may be explained by a lower non-performing asset exposure of highly environmentally engaged banks, especially when the welfare costs of climate change increase. As suggested by Lamperti et al. (2021), environmental risks have a direct impact on GDP growth, increase financial risk and instability, and lead to growing default probabilities in banks. Except for the overall environmental pillar (Column V in Table 5), where the interaction with climate costs is not

Table 5

Non-performing loans as the economic channel. This table reports the estimates of the OLS regression for 2003–2019. The dependent variable is the non-performing loans ratio (*Npl_ratio*, columns I to IV), or the PD (columns V to VIII). The variables of interest are: the *Env* score - columns I and V; the *Env_inn* score – columns II and VI, *Prod_Res* – columns III and VII, and *Res_Red* – columns IV and VIII. Each target variable is interacted with *Climate_costs*. Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one period with respect to the dependent variable. The control variables based on accounting data (*Size*, *Roa*, *Liq*, *Llr_gl*, *Eta*, *Div, Cir*) are winsorized at the 1% of each tail. Bank and time fixed-effects (FE) are included in all specifications. Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Variables	Npl_ratio (I)	(II)	(III)	(IV)	PD (V)	(VI)	(VII)	(VIII)
Climate_costs*Env (-1)	−0.00180**				−0.00114			
	(0.000798)				(0.000749)			
Env (-1)	0.0104				−0.0121*			
	(0.0107)				(0.00665)			
Climate_costs*Env_inn (-1)		−0.00104***				−0.000720**		
		(0.000392)				(0.000333)		
Env_inn (-1)		0.00797				−0.00188		
		(0.0126)				(0.00441)		
Climate_costs*Prod_res (-1)			−0.0688***				−0.0468**	
			(0.0255)				(0.0209)	
Prod_res (-1)			0.00766				0.00196	
			(0.00664)				(0.00326)	
Climate_costs*Res_red				−0.0578*				−0.0625**
				(0.0311)				(0.0293)
Res_red (-1)				0.000164				0.000136
				(0.00365)				(0.00286)
Climate_costs	0.124*	0.159**	0.168**	0.162**	0.0571	0.0881	0.0897	0.107*
	(0.0503)	(0.0524)	(0.0508)	(0.0540)	(0.0584)	(0.0616)	(0.0583)	(0.0585)
Npl_ratio (-1)					0.121***	0.121***	0.120***	0.122***
					(0.0268)	(0.0268)	(0.0266)	(0.0268)
Controls (-1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,317	5,317	5,317	5,317	5,317	5,317	5,317	5,317
R-squared	0.752	0.751	0.751	0.751	0.773	0.772	0.772	0.772

Table 6

Heckman two-step method. This table reports the results obtained from the second step of the Heckman two-step model for the period 2003–2019. The dependent variable is the PD. The variables of interest are: the *Env* score - column I; the *Env_inn* score – column II, *Prod_Res* – column III, and *Res_Red* – column IV. Each target variable is interacted with *Climate_costs*. Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one period with respect to the dependent variable. The control variables based on accounting data (*Size*, *Roa*, *Liq*, *Llr_gl*, *Eta*, *Div, Cir*) are winsorized at the 1% of each tail. Bank and time fixed-effects (FE) are included in all specifications. Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Variables	PD (I)	(II)	(III)	(IV)
Climate_costs*Env (-1)	−0.000860**			
	(0.000371)			
Env (-1)	−0.00106			
	(0.00497)			
Climate_costs*Env_inn (-1)		−0.00147**		
		(0.000730)		
Env_inn (-1)		−0.0109		
		(0.00697)		
Climate_costs*Prod_res (-1)			−0.0554***	
			(0.0208)	
Prod_res (-1)			0.00321	
			(0.00328)	
Climate_costs*Res_red				−0.0684**
				(0.0289)
Res_red (-1)				−0.00149
				(0.00312)
Climate_costs	0.102*	0.0714	0.109**	0.129**
	(0.0518)	(0.0501)	(0.0505)	(0.0535)
IMR	0.00707	0.00761	0.00699	0.00772
	(0.00830)	(0.00802)	(0.00832)	(0.00831)
Controls (-1)	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes
Obs.	5,317	5,317	5,317	5,317
R-squared	0.751	0.752	0.751	0.751

statistically significant, results confirm the robustness of our main results.

Finally, we confirm the significant correlation between the NPL ratio and the probability of default across all specifications of Table 5.

5.2. Robustness checks

In this section we report the results of a set of robustness tests, addressing sample selection bias, unobservable confounding factors, endogeneity, dependency from the selection of metrics used in our econometric setup, and the country-level or banks' business models heterogeneity.

First, we control for sample selection bias employing the Heckman (1978) two-step method (Shen et al., 2016; McGuinness et al., 2017). As a first step we estimate the inverse mills ratio (IMR), running a probit regression. In this setting, the dependent variable is the dummy *High_Env* (Jo and Harjoto, 2011) which takes the value of 1 for banks above the mean value of the sample and 0 otherwise. Secondly, we include IMR as the additional explanatory variable in the performance equation, the OLS regression with bank and time fixed effects (Li and Prabhala, 2007).

Table 6 provides the results of this analysis, supporting the unbiasedness of our sample. We confirm the significant negative relationship between the environmental variables (*Env, Env_inn, Prod_Res* and *Res_red*) and default probabilities of banks.[10]

Additionally, we check if estimators are biased by overlooking unobservable confounding factors (Chen et al., 2020). We consider that bank decisions to adopt specific environmental policies may be a consequence of unobserved banks characteristics that also affect the probability of default. Therefore, we address this concern by running a weighted OLS regression employing a propensity score matching (PSM) procedure on all bank controls. We first match each treated bank (above the mean value of the ENV score) to a control bank using Caliper 2 % matching, allowing for replacement (Chen et al., 2018). We then run again Equation (1), checking the consistency of results. As shown in Table 7, the results for PSM weighted regression confirm a correlation between sustainability and stability in banks.

[10] In further testing, we address differences in governance structures and business models across banks (e.g., Islamic banks and non-traditional banking). We add controls based on the Islamic Finance Development Index of *Refinitiv* (Paltrinieri et al., 2020). We also consider governance dimensions and bank government ownership. Results, available upon reasonable request are consistent with baseline results.

Table 7

PSM weighted regression. This table reports the results of the weighted regression obtained after running the Propensity Score Matching (PSM) procedure over the sample period (2003–2019). The variables of interest are: the *Env* score - column I; the *Env_inn* score – column II, *Prod_Res* – column III, and *Res_Red* – column IV. Each target variable is interacted with *Climate_costs*. Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one period with respect to the dependent variable. The control variables based on accounting data (*Size*, *Roa*, *Liq*, *Llr_gl*, *Eta*, *Div, Cir*) are winsorized at the 1% of each tail. Bank and time fixed-effects (FE) are included in all specifications. Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Variables	PD (I)	(II)	(III)	(IV)
Climate_costs*Env (-1)	−0.00108***			
	(0.000302)			
Env (-1)	−0.000382			
	(0.00627)			
Climate_costs*Env_inn (-1)		−0.00166**		
		(0.000736)		
Env_inn (-1)		−0.00941		
		(0.00855)		
Climate_costs*Prod_res (-1)			−0.0778**	
			(0.0327)	
Prod_res (-1)			0.00460	
			(0.00410)	
Climate_costs*Res_red				−0.0987***
				(0.0258)
Res_red (-1)				0.00105
				(0.00371)
Climate_costs	0.0739	0.0336	0.0878	0.116**
	(0.0524)	(0.0529)	(0.0534)	(0.0566)
Controls (-1)	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes
Obs.	3,972	3,972	3,972	3,972
R-squared	0.742	0.743	0.741	0.742

Endogeneity problems may be still present in our estimates from omitted variables, which neither the Heckman two-step approach nor the PSM regression specifically address. Therefore, we follow the literature (Chiaramonte et al., 2022; Anginer et al., 2018) and perform an instrumental variable two-stage regression (IV 2SLS) to check if our results suffer from this bias.

The crucial task in an IV 2SLS regression is choosing an instrument that is strongly correlated with the instrumented variable (*Env, Env_inn, Prod_Res* and *Res_red*) but not correlated with the dependent variable (PD). Therefore, as in Anginer et al. (2018), we use the country and year average values of *Env, Env_inn, Prod_Res* and *Res_red* variables as instruments, being highly correlated to bank environmental policies but not with *PD*, and finally run the IV 2SLS regression.

As shown in Panel A of Table 8, the first stage of the IV 2SLS regression confirms the validity of the selected instruments, being positively and statistically significantly correlated with the instrumented variable (*Env, Env_inn, Prod_Res* and *Res_red)*. As for the second stage, panel B shows that banks more engaged in environmental practices have a lower PD when climate change welfare costs increase, confirming our earlier results.

Additionally, our baseline results may depend on the selected measures of bank stability. Therefore, we rerun our Equation (1) using alternative measures of bank stability and risks. We follow the literature (Anginer et al., 2018) by using the one-year Merton's distance to default (DTD) as an alternative stability measure, and the volatility of returns (VOL) of Cabrera et al., (2018), as measures of bank risk. Both variables are measured on a quarterly frequency.

As reported in Table 9 on the basis of almost 7,000 observations, the coefficients of our environmental variables (*Env*, *Env_inn, Prod_res* and *Res_*red) are still negatively and statistically significantly correlated to the DTD and VOL. Further, the largest coefficients are those attributed to resource reduction policy financing (*Res_red*), followed by bank product environmental responsible policy investments (*Prod_res*), environmental innovation (*Env_inn*), and the overall ENV score.

An additional concern is that our findings may arise from having assessed the sustainability-stability relationship by using only four measures of engagement. To address this issue, we check the robustness of our baseline analysis by using alternative measures of environmental engagement: the Bloomberg ENV score (*BEnv).* This is a measure focusing on transparency rather than engagement, as it is the case for Thomson Reuters metrics. We also use Bloomberg's carbon price policy (*Carbon_price*), and equator environmental principles financing policy (*Equator_princ*). These three alternative measures allow us to check the consistency of our results by using other proxies for sustainability practices. Table 10 shows the results of this additional test, demonstrating that our findings are robust to changes in measures of banks' environmentalism.

As an additional check, we aim at exploring the relationship between climate change, environmental engagement, and stability by using an alternative measure of the country-level impact of climate change. Therefore, we adopt abnormal level of surface temperature (*Abn_temp*) as provided by OECD. This frequently used measure reports annual changes compared to the 1951–1980 average surface

Table 8

IV 2SLS. This table reports the results of the instrumental variable two-stage least square (IV 2SLS) procedure over the sample period (2003–2019). Panel A shows the results for the first stage, where the target variables are the instruments for *Env, Env_inn, Prod_res and Res_red* (*Instr_Env, Instr_Env_inn, Instr_Prod_res and Instr_Res_red*). Panel B shows the results for the second stage, where variables of interest are: the *Env* score - column I; the *Env_inn* score – column II, *Prod_Res* – column III, and *Res_Red* – column IV. Each target variable is interacted with *Climate_costs*. Panel B includes the Sargan test (Sargan *p*-value) of over-identifying restrictions. Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one period with respect to the dependent variable. Control variables based on accounting data (*Size, Roa, Liq, Llr_gl, Eta, Div, Cir*) are winsorized at the 1% of each tail. Bank and time fixed-effects (FE) are included in all specifications. Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Panel A: First stage				
	Env	Env_inn	Prod_res	Res_red
Variables	(I)	(II)	(III)	(IV)
Instr_Env (-1)	0.673***			
	(0.0533)			
Instr_Env_inn (-1)		0.758***		
		(0.0574)		
Instr_Prod_res (-1)			0.695***	
			(0.0446)	
Instr_Res_red (-1)				0.612***
				(0.0584)
Controls (-1)	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes
Obs.	5,317	5,317	5,317	5,317
F-Cragg Donald test	749***	748***	751***	750***

Panel B: Second stage				
	PD			
Variables	(I)	(II)	(III)	(IV)
Climate_costs*Env (-1)	−0.00361**			
	(0.00178)			
Env (-1)	−0.00360			
	(0.00842)			
Climate_costs*Env_inn (-1)		−0.00225***		
		(0.000520)		
Env_inn (-1)		0.00620		
		(0.00502)		
Climate_costs*Prod_res (-1)			−0.0523**	
			(0.0234)	
Prod_res (-1)			0.00286	
			(0.00326)	
Climate_costs*Res_red				−0.141***
				(0.0523)
Res_red (-1)				0.00213
				(0.00373)
Climate_costs	0.0772	0.159***	0.107**	0.194***
	(0.0513)	(0.0527)	(0.0510)	(0.0683)
Controls (-1)	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes
Obs.	5,317	5,317	5,317	5,317
Sargan p-value	0.171	0.100	0.721	0.150

Table 9
Alternative measures of banks stability and risk. This table reports the estimates of the OLS regression for the sample period (2003–2019). The dependent variable is the Merton's distance to default (*DTD*, Columns 1–4) and volatility of quarterly returns (*VOL*, Columns 5–8), measuring bank stability and risk. The variables of interest are: the *Env* score (Columns 1 and 5); the *Env_inn* score (Columns 2 and 6, *Prod_Res* – Columns III and VII, and *Res_Red* - columns IV and VIII. Each target variable is interacted with *Climate_costs.* Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one period with respect to the dependent variable. The control variables based on accounting data (*Size*, *Roa*, *Liq*, *Llr_gl*, *Eta*, *Div, Cir*) are winsorized at the 1% of each tail. Bank and time fixed effects (FE) are included in all specifications. Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Variables	DTD (I)	(II)	(III)	(IV)	VOL (V)	(VI)	(VII)	(VIII)
Climate_costs*Env (-1)	−0.0265*				−0.00572**			
	(0.0139)				(0.00272)			
Env (-1)	0.000406				−9.29e-05			
	(0.00145)				(0.000267)			
Climate_costs*Env_inn (-1)		−0.0177***				−0.00341***		
		(0.00441)				(0.00100)		
Env_inn (-1)		0.00109				0.000107		
		(0.000931)				(0.000199)		
Climate_costs*Prod_res (-1)			−1.414***				−0.296***	
			(0.397)				(0.0716)	
Prod_res (-1)			0.108				0.0216*	
			(0.0705)				(0.0118)	
Climate_costs*Res_red				−1.739***				−0.344***
				(0.632)				(0.128)
Res_red (-1)				0.0644				0.0125
				(0.0823)				(0.0124)
Climate_costs	0.650	1.191	1.602*	2.125**	−0.0926	0.00622	0.108	0.199
	(0.812)	(0.824)	(0.867)	(0.953)	(0.149)	(0.158)	(0.167)	(0.191)
Controls (-1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6,979	6,979	6,979	6,979	6,950	6,950	6,950	6,950
R-squared	0.734	0.734	0.737	0.735	0.735	0.735	0.737	0.736

Table 10
Alternative measures of environmental engagement. This table reports the estimates of the OLS regression for the sample period (2003–2019). The dependent variable is the probability of default (PD) which measures bank stability. The variables of interest include the Bloomberg environmental score (*BEnv*) - column I; the *Carbon_price* and the *Equator_princ* variables - columns II and III, respectively. Each target variable is interacted with *Climate_costs*. Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one period with respect to the dependent variable. The control variables based on accounting data (*Size*, *Roa*, *Liq*, *Llr_gl*, *Eta*, *Div, Cir*) are winsorized at the 1% of each tail. Bank and time fixed effects (FE) are included in all specifications. Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Variables	PD (I)	(II)	(III)
Climate_costs*BEnv (-1)	−0.00236**		
	(0.00105)		
BEnv (-1)	−0.000164		
	(0.000150)		
Climate_costs*Carbon_price (-1)		−0.0548**	
		(0.0263)	
Carbon_price (-1)		0.0145	
		(0.00998)	
Climate_costs*Equator_princ (-1)			−0.0914*
			(0.0466)
Equator_princ (-1)			0.00588
			(0.00393)
Climate_costs	0.0628	0.0713	0.0681
	(0.0516)	(0.0508)	(0.0508)
Controls (-1)	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes
Obs.	4,339	5,317	5,317
R-squared	0.771	0.750	0.751

Table 11

Alternative measure of climate change: country-level abnormal surface temperature. This table reports the estimates of the OLS regression for the sample period (2003–2019) using the abnormal surface temperature as an alternative metric for climate change. The dependent variable is the probability of default (PD) which measures bank stability. The variables of interest are: the *Env* score - column (I); the *Env_inn* score – column II, *Prod_Res* – column III, and *Res_Red* – column IV. Each target variable is interacted with *Abn_temp*. Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one period with respect to the dependent variable. The control variables based on accounting data (*Size*, *Roa*, *Liq*, *Llr_gl*, *Eta*, *Div, Cir*) are winsorized at the 1% of each tail. Bank and time fixed effects (FE) are included in all specifications. Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Variables	PD (I)	(II)	(III)	(IV)
Abn_temp*Env (-1)	−0.0016**			
	(0.0005)			
Env (-1)	−0.0001			
	(0.0001)			
Abn_temp*Env_inn (-1)		−0.0017**		
		(0.0006)		
Env_inn (-1)		0.0001		
		(0.0002)		
Abn_temp*Prod_res (-1)			−0.00178	
			(0.00377)	
Prod_res (-1)			0.00137	
			(0.00488)	
Abn_temp*Res_red				0.00293
				(0.00406)
Res_red (-1)				−0.00792
				(0.00578)
Abn_temp (-1)	0.00301*	0.00241	0.00337	0.000468
	(0.00174)	(0.00177)	(0.00253)	(0.00310)
Controls (-1)	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes
Obs.	5,317	5,317	5,317	5,317
R-squared	0.753	0.752	0.749	0.750

Table 12

Environmental engagement for different sub-samples. This table reports the estimates of the OLS regression for our sample period (2003–2019) distinguishing main differences in bank business models (below and above the mean value of DIV) and country income level (GDP_PC). The dependent variable is the probability of default (PD) which proxies bank stability. The variables of interest are *Env* interacted with *Climate_costs* (which measures the country-level costs of climate change). Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one period with respect to the dependent variable. Control variables based on accounting data (*Size*, *Roa*, *Liq*, *Llr_gl*, *Eta*, *Div*, *Cir*) are winsorized at the 1% of each tail. Bank and time fixed-effects (FE) are included in all specifications. Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

	PD Below DIV	Above DIV	Below GDP_PC	Above GDP_PC
Variables	(I)	(II)	(III)	(IV)
Climate_costs*Env (-1)	−0.00215**	0.0001	−0.00151*	0.000117
	(0.000928)	(0.00111)	(0.000834)	(0.00161)
Controls (-1)	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes
Obs.	2,105	3,212	3,013	2,304
R-squared	0.849	0.710	0.682	0.842

temperature, as a measure of climate change effects. Positive values reflect hotter temperature anomalies. Table 11 shows the results of this additional analysis.

We find that *Env* and *Env_inn* are the variables that, interacted with this alternative measure of climate change, are associated with a reduction in banks default probabilities. We attribute the lack of statistical significance for the other two variables (*Res_red* and *Prod_res*) to the non-linear and lagging relationship that abnormal temperatures have with financing and investing resource-use reduction practices or environmentally responsible products.

Finally, we explore if the environmental engagement-PD relationship changes across banking business model (above versus below mean levels of the non-interest income scaled by the operating income, *DIV*) and country-level per-capita gross domestic product (*GDP_PC*). In doing so, we check if the documented relationship changes for banks with greater reliance on non-interest revenue sources (above the average value of *DIV*), by being less exposed to lending operations (Reghezza et al., 2022). As for the *GDP_PC* analysis, it allows us to check cross-country income level effects distinguishing between more and less economically developed countries.

Results, displayed in Table 12, show that banks with less non-interest income and headquartered in lower income countries mostly benefit from the environmental engagement-PD relationship, supporting the policy relevance of banks' environmentalism. Overall, our findings robustly evidence that banks' engagement towards sustainability is important for financial stability.

6. Conclusions

Climate change concerns increasingly motivate scholarly interest. We focus on bank environmental engagement and its impact on financial stability. We find that environmental performance, proxied by sustainability scores and policies, serves as a climate change risk hedging strategy. Moreover, we find that a viable economic channel for this relationship is the asset quality in banks, proxied by non-performing loans. We show that the overall environmental scores, environmental innovation scores, resource reduction policy, and environmental responsible products reflect bank-specific policies that explain both average and marginal higher stability in a context of increasing climate change risks and exposures.

By using an unbalanced cross-country dataset of 5,317 bank-quarter observations from 2003 to 2019, and by employing different econometric strategies, we find that costs related to climate change increase bank probabilities of default. Bank-level environmental practices reduce this detrimental effect, especially after natural and climate-related disasters. Specifically, we find that after major regional natural disasters, the marginal lower probability of default of more environmentally friendly banks spans from 8 to 29 %.

We extend the literature on climate change implications for bank stability by empirically addressing the role played by environmental policies when climate change costs increase, suggesting useful policy implications for countries that are increasingly exposed to climate-change induced natural disasters.

Our results also demonstrate how asset managers and investors may reduce climate change risks of their portfolios by investing in banks with higher engagement in environmental policies, or similarly to banks managers on how to contribute to the mitigation of financial instability by considering sustainability practices to a larger extent.

CRediT authorship contribution statement

Laura Chiaramonte: . **Alberto Dreassi:** . **John W. Goodell:** . **Andrea Paltrinieri:** . **Stefano Piserà:** Data curation, Investigation, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

A.1 Correlation matrix

This table provides the correlation matrix for our main dependent, target, and control variables. Superscripts (*) denote statistical significance at the 5 % level.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	PD	1													
2	Env	0.2834*	1												
3	Env_innov	0.2351*	0.9067*	1											
4	Prod_resp	0.2004*	0.7252*	0.7491*	1										
5	Res_red	0.1890*	0.6926*	0.6068*	0.6330*	1									
6	Climate_costs	−0.1242*	−0.0128	−0.0113	−0.0186*	0.0205*	1								
7	Abn_temp	−0.0140	0.5533*	0.5806*	0.4860*	0.4092*	−0.0000	1							
8	Size	0.1557*	0.5021*	0.4032*	0.4268*	0.4856*	−0.0010	0.2747*	1						
9	Roa	−0.2403*	−0.0252*	−0.0554*	−0.0523*	0.0207*	0.0879*	0.0064	0.0670*	1					
10	Llr_gl	0.1315*	0.0439*	0.0354*	0.0524*	0.0912*	−0.0074	0.0156	0.0446*	0.0552*	1				
11	Liq	0.0384*	0.1413*	0.1240*	0.2118*	0.2519*	−0.0267*	0.0216*	0.2850*	0.1778*	0.0807*	1			
12	Div	−0.0464*	0.3123*	0.2485*	0.1674*	0.2424*	−0.1827*	0.2073*	0.2892*	0.0444*	0.0025	0.1498*	1		
13	Cir	0.2580*	0.2504*	0.2113*	0.1456*	0.1617*	−0.0309*	0.0124	0.0645*	−0.1084*	0.0712*	−0.0236*	0.0561*	1	
14	Eta	−0.2662*	−0.2712*	−0.2463*	−0.1801*	−0.1796*	0.0147*	−0.1799*	−0.2118*	0.3858*	0.0953*	0.0324*	−0.0201*	−0.1340*	1

A.2 Baseline results with alternative fixed effects and additional country controls

This table reports the estimates of the OLS regression for 2003–2019 using country*quarter FE and additional country controls (D_Bank crisis, Inflation and GDP growth (GDP_Grw). The dependent variable is the probability of default (PD) which measures a bank's stability. The variables of interest are: the *Env* score - column (I); the *Env_inn* score, *Prod_Res* and *Res_Red* - columns (II), (III), and (IV), respectively. Each target variable is interacted with *Climate_costs* (which measures the country-level costs of climate change). Variable definitions are provided in Table 1. All non-binary independent variables are lagged by one period with respect to the dependent variable. The control variables based on accounting data (*Size*, *Roa*, *Liq*, *Llr_gl*, *Eta*, *Div*, *Cir*) are winsorized at the 1 % of each tail and included in all specifications. Bank clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1 %, 5 %, and 10 % levels, respectively, in two-tailed tests.

Variables	PD (I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Climate_costs*Env (-1)	−0.000826***				−0.00151*			
	(0.000313)				(0.000786)			
Climate_costs*Env_inn (-1)		−0.000488**				−0.000922**		
		(0.000201)				(0.000365)		
Climate_costs*Prod_res (-1)			−0.0370***				−0.0573***	
			(0.0139)				(0.0216)	
Climate_costs*Res_red				−0.0829***				−0.0695**
				(0.0200)				(0.0315)
D_Bank crisis					−0.000419	−0.000133	−0.000273	−0.000555
					(0.00430)	(0.00424)	(0.00422)	(0.00430)
Inflation (-1)					0.000530	0.000566	0.000710	0.000617
					(0.00113)	(0.00116)	(0.00113)	(0.00116)
GDP_Grw (-1)					0.000212	0.000129	0.000192	0.000239
					(0.000754)	(0.000738)	(0.000734)	(0.000751)
Controls (-1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country*Quarter FE	Yes	Yes	Yes	Yes	No	No	No	No
Bank and Quarter FE	No	No	No	No	Yes	Yes	Yes	Yes
Cluster S.E Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,317	5,317	5,317	5,317	3,293	3,293	3,293	3,293
R-squared	0.704	0.702	0.702	0.702	0.687	0.686	0.687	0.687

A.3 Country and regional sample breakdown

This table reports the number of observations in our sample, and their share, broken down by country and by continent.

Region	N. of Obs	%
Asia	978	18.39
Europe	2,083	39.18
Oceania	236	4.44
South America	212	3.99
United States	1,808	34.00
Total	5,317	100.00
Country of Headquarters		
Australia	228	4.29
Austria	128	2.41
Chile	69	1.30
Colombia	98	1.84
Czech Republic	9	0.17
Denmark	107	2.01
Finland	62	1.17
France	136	2.56
Germany	202	3.80
Hungary	34	0.64
Ireland; Republic of	140	2.63
Israel	112	2.11
Italy	243	4.57
Japan	866	16.29
Mexico	45	0.85
Netherlands	27	0.51

(*continued on next page*)

(*continued*)

Region	N. of Obs	%
Norway	21	0.39
Poland	308	5.79
Portugal	66	1.24
Spain	157	2.95
Sweden	54	1.02
Switzerland	44	0.83
Turkey	67	1.26
United Kingdom	286	5.38
United States of America	1,808	34.00
Total	5,317	100.00

The authors affirm that this work is an original work that is not published or under consideration elsewhere and is a genuine collaboration.

References

Ahonen, E., Corbet, S., Goodell, J.W., Günay, S., Larkin, C., 2022. Are carbon futures prices stable? New evidence during negative oil. Finance Research Letters 102723.

Anginer, D., Demirguc-Kunt, A., Huizinga, H., Ma, K., 2018. Corporate governance of banks and financial stability. Journal of Financial Economics 130 (2), 327–346.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., Visentin, G., 2017. A climate stress-test of the financial system. Nature Climate Change 7, 283–288.

Bird, D.K., Haynes, K., van den Honert, R., McAneney, J., Poortinga, W., 2014. Nuclear power in Australia: A comparative analysis of public opinion regarding climate change and the Fukushima disaster. Energy Policy 65, 644–653.

Bondioli, M., Goldberg, M., Hu, N., Li, C., Maalaoui, O., Maalaoui, O., Stein, H. J., 2021. The Bloomberg Corporate Default Risk Model (DRSK) for Public Firms. Available at SSRN: https://ssrn.com/abstract=3911300 or https://doi.org/10.2139/ssrn.3911300.

Bouslah, K., Kryzanowski, L., M'Zali, B., 2018. Social performance and firm risk: Impact of the financial crisis. Journal of Business Ethics 149, 643–669.

Cabrera, M., Dwyer, G., P. and Nieto, M. J, 2018. The G-20′s regulatory agenda and banks' risk. Journal of Financial Stability 39 (December), 66–78.

Caby, J., Ziane, Y., Lamarque, E., 2022. The impact of climate change management on banks profitability. Journal of Business Research 142 (March), 412–422.

Chen, I.-J., Hasan, I., Lin, C.-Y., Nguyen, T.N.V., 2020. Do banks value borrowers' environmental record? Evidence from financial contracts. Journal of Business Ethics 174, 687–713.

Chen, Y.C., Hung, M., Wang, Y., 2018. The effect of mandatory CSR disclosure on firm profitability and social externalities: Evidence from China. Journal of Accounting and Economics 65 (1), 169–190.

Cheung, A., 2016. Corporate social responsibility and corporate cash holdings. Journal of Corporate Finance 37 (April), 412–430.

Chiaramonte, L., Dreassi, A., Girardone, C., Piserà, S., 2022. Do ESG strategies enhance bank stability during financial turmoil? Evidence from Europe. European Journal of Finance 28, 1173–1211.

Cisl, 2015. Unhedgeable risk: How climate change sentiment impacts investment. University of Cambridge Institute for Sustainability Leadership, Technical Report, December.

Corbet, S., Goodell, J.W., Günay, S., 2020. Co-movements and spillovers of oil and renewable firms under extreme conditions: New evidence from negative WTI prices during COVID-19. Energy Economics 92, 104978.

Dafermos, Y., Nikolaidi, M., Galanis, G., 2018. Climate change, financial stability and monetary policy. Ecological Economics 152, 219–234.

Dell, M., Jones, B.F., Olken, B.A., 2012. Temperature shocks and economic growth: evidence from the last half century. American Economic Journal: Macroeconomics 4 (3), 66–95.

Dunz, N., Naqvi, A., Monasterolo, I., 2021. Climate sentiments, transition risk, and financial stability in a stock-flow consistent model. Journal of Financial Stability 54 (June).

Duqi, A., McGowan, D., Onali, E., Torluccio, G., 2021. Natural disasters and economic growth: The role of banking market structure. Journal of Corporate Finance 71 (December).

Eichler, S., Sobański, K., 2016. National politics and bank default risk in the eurozone. Journal of Financial Stability 26, 247–256.

Gbd, 2019. The lancet global burden of disease. Technical Report, GBD Resource Center.

Heckman, J.J., 1978. Dummy endogenous variables in a simultaneous equation system. Econometrics 46 (4), 931–959.

Huang, Q., Li, Y., Lin, M., McBrayerd, G.A., 2022. Natural disasters, risk salience, and corporate ESG disclosure. Journal of Corporate Finance 72 (February).

Jo, H., Harjoto, M.A., 2011. Corporate governance and firm avlue: The impact of corporate social responsibility. Journal of Business Ethics 103, 351–383.

Klomp, J., 2014. Financial Fragility and Natural Disasters. An Empirical Analysis. Journal of Financial Stability 13, 180–192.

Lamperti, F., Bosetti, V., Roventini, A., Tavoni, M., Treibicha, T., 2021. Three green financial policies to address climate risks. Journal of Financial Stability 54 (June).

Li, K. and Prabhala, N. R., 2007. Self-selection models in corporate finance. Handbooks in Finance, Handbook of Empirical Corporate Finance, Volume 1, Chapter 2: 37-86, https://doi.org/10.1016/B978-0-444-53265-7.50016-0.

Liang, H., Renneboog, L., 2017. On the Foundations of Corporate Social Responsibility. Journal of Finance 72 (2), 853–910.

Lins, K.V., Servaes, H., Tamayo, A., 2017. Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility During the Financial Crisis. Journal of Finance 72 (4), 1785–1823.

McGuinness, P.B., Vieito, J.P., Wang, M., 2017. The Role of Board Gender and Foreign Ownership in the CSR Performance of Chinese Listed Firms. Journal of Corporate Finance 42, 75–99.

Mercure, J.F., Pollitt, H., Viñuales, J.E., Edwards, N.R., Holden, P.B., Chewpreecha, U., Salas, P., Sognnaes, I., Lam, A., Knobloch, F., 2018. Macroeconomic impact of stranded fossil fuel assets. Nature Climate Change 8 (7), 588–593.

Monasterolo, I., Raberto, M., 2017. Is there a role for Central Banks in the low-carbon transition? A stock-flow consistent modelling approach. SSRN Working Paper (November, 21).

Noth, F., Schüwer, U., 2023. Natural disasters and bank stability: Evidence from the U.S. financial system. Journal of Environmental Economics and Management 119, 102792.

Paltrinieri, A., Dreassi, A., Migliavacca, M., Piserà, S., 2020. Islamic finance development and banking ESG scores: Evidence from a cross-country analysis. Research in International Business and Finance 51, 101100.

Poortinga, W., Aoyagi, M., Pidgeon, N.F., 2013. Public perceptions of climate change and energy futures before and after the Fukushima accident: A comparison between Britain and Japan. Energy Policy 62, 1204–1211.

Reghezza, A., Altunbas, Y., Ibanez, D.-M., d'Acri, C.,R., Spaggiari, M., 2022. Do banks fuel climate change? Journal of Financial Stability 62 (101049), 1572–3089.

Roy, R. and Braathen, N. A., 2017. The rising cost of ambient air pollution thus far in the 21st Century: Results from the BRIICS and the OECD Countries. OECD Environment Working Papers, no. 124, OECD Publishing, Paris.

Schüwer, U., Lambert, C., Noth, F., 2019. How do banks react to catastrophic events? Evidence from Hurricane Katrina. Review of Finance 23 (1), 75–116.

Shen, C.H., Wu, M.W., Chen, T.H., Fang, H., 2016. To engage or not to engage in corporate social responsibility: Empirical evidence from global banking sector. Economic Modelling 55, 207–225.

Stiglitz, J., Stern, N., Duan, M., Edenhofer, O., Giraud, G., Heal, G., Lèbre la Rovere, E., Morris, A., Moyer, E., Pangestu, M., Shukla, P., Sokona, Y., Winkler, H., 2017. Report of the high-level commission on carbon prices. Technical Report, Carbon Pricing Leadership Coalition.