Climate Change As a New Source of Systemic Risk: An Empirical Analysis of Climate Risk Drivers for European Banks

Claudia Cannas*

January 15, 2025

Abstract

In the aftermath of Paris Agreement in 2015, the assessment and monitoring of climate-related and environmental risks has been considered at the centre of the financial debate in Europe. Extreme environmental events related to climate change significantly increase environmental cost for governments and interest expenses for banks with a negative effect on their balance sheets. Focusing on a panel dataset of 79 listed banks over the period 2005:Q1 and 2023:Q3, I analyse how a set of traditional variables at bank level in systemic risk literature and macroeconomic indicators may impact on a climate risk indicator, namely CRISK, recently introduced in the econometrics literature by Jung et al. (2021) which extends the SRISK methodology (Acharya et al., 2012; Brownlees & Engle, 2017). Our results determine several policy implications especially for larger bank which are likely to be more exposed to brown industries. Finally, the study claims to an effective action by central banks and financial authorities beyond the design climate-related financial risks policies and strategies in order to sensitize and attract investors to accelerate investment in transition of the economy and safeguard environmental and financial stability.

Keywords: Climate risk, Climate change, Financial Stability, Climate Policies, European banks.

J.E.L. Classification Numbers: E44, G10, Q54.

* Department of Political Economy and CSEA, Catholic University of Sacred Heart, Milan, Italy.

Climate Change As a New Source of Systemic Risk: An Empirical Analysis of Climate Risk Drivers for European Banks

Abstract

In the aftermath of Paris Agreement in 2015, the assessment and monitoring of climate-related and environmental risks has been considered at the centre of the financial debate in Europe. Extreme environmental events related to climate change significantly increase environmental cost for governments and interest expenses for banks with a negative effect on their balance sheets. Focusing on a panel dataset of 79 listed banks over the period 2005:Q1 and 2023:Q3, I analyse how a set of traditional variables at bank level in systemic risk literature and macroeconomic indicators may impact on a climate risk indicator, namely CRISK, recently introduced in the econometrics literature by Jung et al. (2021) which extends the SRISK methodology (Acharya et al., 2012; Brownlees & Engle, 2017). Our results determine several policy implications especially for larger bank which are likely to be more exposed to brown industries. Finally, the study claims to an effective action by central banks and financial authorities beyond the design climate-related financial risks policies and strategies in order to sensitize and attract investors to accelerate investment in transition of the economy and safeguard environmental and financial stability.

Keywords: Climate risk, Climate change, Financial Stability, Climate Policies, European banks.

J.E.L. Classification Numbers: E44, G10, Q54.

1 Introduction

Floods, storms, biodiversity loss are just a few direct consequences of the climate change, whereas the relevant environmental cost for governments and interest expenses for banks are not likely to be more dramatic. Measuring and monitoring climate-related and environmental risks has assumed increasing importance worldwide, especially in Europe, whereas the European Central Bank strictly oversees their potential impact on the broader economy and financial stability. Increasingly put at the centre of the financial debate (Carney, 2015; of England, 2018), climate-related and environmental risks are commonly understood to involve two main risk drivers as well as physical risk and transition risk (Bank, 2020). The first one refers to the financial impact of a changing climate (extreme weather events and gradual changes in climate, environmental degradation, biodiversity loss and deforestation). While, the transition risk concerns an institution's financial loss resulting, directly or indirectly, from the process of adjustment towards a lower-carbon and more environmentally sustainable economy. Within the last stress test of ECB, the same financial authority claims for an immediate action to challenge physical and transition risks arguing that whether current emission trends were to continue globally and significant pressure on biodiversity were to be maintained, banks in the euro area would record on average losses almost three times higher than those expected in a future resource-efficient scenario, in line with the 2015 Paris Agreement (Bank, 2024). Building on the recent concept of climate stress test of the financial system (Battiston et al., 2017), the importance of climate stress-testing for financial stability is now widely recognized by financial supervisors (Allen et al., 2020; Bolton et al., 2020; NGFS, 2021). In this context, the prioritised vulnerability of climate and environmental risks finds support within the Supervisory priorities for 2024-2026 , where these issues have been moved from the "Priority 3" to "Priority 2" compared to Supervisory priorities for 2022-2024. Among the three priorities[1], ECB claims that banks should adequately incorporate Climate and Environmental risks within their business

[1] The priorities promote effectiveness and consistency in the supervisory planning of the Joint Supervisory Teams (JSTs) and support a more efficient allocation of resources, in line with the setting of the corresponding risk tolerance levels (Bank, 2023). Specifically, "*Priority 1*" consists of Strengthening resilience to immediate macro-financial and geopolitical shocks. "*Priority 2*" aims to Accelerate the effective remediation of shortcomings in governance and the management of climate-related and environmental risks. "*Priority 3*" addresses the further progress in digital transformation and building robust operational resilience frameworks.

strategy and their governance and risk management frameworks in order to mitigate and disclose such risks, aligning their practices with current regulatory requirements and supervisory expectations. Delayed climate action is expected to further increase physical and transition risks and, potentially, the related losses to banks, raising the risk of greater damages, locked-in high emission infrastructures, stranded assets and cost escalation. The growing importance to assess and monitor climate-related and environmental risks both for scholars and practitioners, has provided first interesting findings in academic literature. According to Battiston (2021) climate change represents the major source of risk for the financial system. Given the significant influence of the adoption of climate and environmental policies (i.e. carbon taxes or green subsidies), environmental technological progress or changes in market sentiment and preferences, the transition risk can have a potential adverse effect on the real economy especially through the banking sector (Jung et al., 2021). Further, Carney et al. (2015) identified a further risk as well as the liability risk. Liability risks are related to financial claims that could occur decades from now, provided that parties who have suffered loss or damage from the effects of climate change are able to seek compensation from those they hold legally responsible. From a broad perspective, relevant evidence came from the multitude of scenarios emerging from the Climate risk stress test lead by the ECB in 2022 reflects the complex nature of the climate risk facing the banking sector. According to ECB, climate change considerations should be involved into analysis and decision-making processes, macroeconomic models, projections and scenarios, financial stability assessment, monetary policy analysis and transmission, risk management framework. However, one of the main challenges for many institutions is climate-related data availability which represents the key driver for the lack of climate risk stress testing. At the reference date (31 December 2021) the percentage of banks without a climate-risk stress testing framework in place is above 50%. Among the main findings of the 2022 CST emerge that around 40% of the banks with a climate risk stress-testing framework in place do not consider climate stress test outcomes when implementing their business strategy, while only 19% of the banks with a CST framework in place use it to inform their loan granting process. ii) 60% of the banks with a climate risk stress-testing framework in place do not currently disclose or intend to disclose any results of the climate risk stress test under Pillar III; iii) although the 93% of the banks with a climate risk stress-testing framework in place have developed a validation process, the 75% of them do not ensure independence between the development and validation processes and the 40% of them do not currently involve the internal audit function in reviewing the framework. Moreover, institutions participating in the 2022 CST differ among them in terms of reliance from GHG-emitting sectors in relation to the business model. The academic literature has outlined that investing in fossil-fuel companies, financial institutions hold direct high-carbon exposures, which for European actors have been estimated to be, relative to their total assets about 1.3% for banks, 5% for pension funds and 4.4% for insurances (Weyzig et al., 2014). The most emitting sectors including mining and quarrying and manufactures of coke, tend to be dominated by large companies which may be more likely to enter into relationships with larger banks or specialised lenders. This could explain why G-SIBs, universal banks and investment banks have more significant exposures to GHG-emitting sectors. Along this line, Battiston et al. (2017) outlined that direct and indirect exposures to such sectors represent portion of banks' loan portfolios comparable their capital. The early and stable implementation of climate policies is crucial for market participants to smoothly anticipate the effects. So, in the 2022 CST exercise, banks were asked to provide information about their long-term strategic plans under the three different scenarios, i.e. orderly, disorderly and hot house world. Yet, several issues remain unaddressed. In particular, the impact on financial stability of the interplay between climate policy shocks and market conditions has not been analysed so far. Recent literature has provided over the last decade strong evidence on climate risk related to the potential adverse effects of climate change on society and the economy in coming decades (Seneviratne et al., 2018). Main concerns seem to be related to the assess of climate risk. Despite others financial risk metrics (i.e. value-at-risk), climate risk cannot be assessed based on past events, since they are not good predictors of the future in this respect. Climate change has affected differently countries and economies with different impacts and consequences. This study contributes to the growing literature on climate risk and financial stability by analysing the main drivers of Climate-related risk exposure for European Banks. In relation to the availability of data, it focuses on panel data sample of 79 European banks between 2005:Q1 and 2023:Q4 in order to analyse whether key climate risk's drivers exist. So, it considers a novel econometrics variable defined by Jung et al. (2021), the climate risk (or CRISK) which is available at the Volatility Laboratory (V-Lab). It represents the expected capital shortfall conditional on the climate stress. So, an increase in CRISK measure represents an increase in climate risk. In line with the previous evidence in literature, among the traditional variables within the systemic risk literature, our outcomes point out that an increase in the banks' size, leverage and market beta contribute to an increase of climate risk for European banks (p-value$<$0.001).. At macro level, I highlight that the rise in the change of the overall inflation (including energy and food prices) and market concentration captured by the Herfindahl Index, tend to increase climate risk (p-value$<$0.001). Contrarily, I evidence that as the short-term liability ratio (STL) and Capital Adequacy ratio Tier 1 (TIER 1) increase, climate risk significantly decreases. Finally, the one-quarter lagged increase in Climate Beta, tends to significantly reduce the dependent variables (p-value $<$ 0.10). The CRISK, which is a function of climate beta is likely to be higher for banks that are larger, more leveraged, and with higher climate beta (Jung et al., 2021). However, as I compare the trends over the time of CRISK and climate beta estimates, I may show that significantly differ between them. I show that Climate beta has a moderating role, contributing to significantly reduce climate risk (p-value $<$ 0.10). To conclude, as the change in GDP increases, climate risk decreases of 0.005 basis points. The R2 (within) is higher than 40% and the robustness of the analysis is supported by robust standard errors and FE estimation. This study contributes to the existing literature providing empirical evidence on the different drivers of climate risk for European banks supporting policy makers in the design of climate-related financial risks strategies. Given the increasing frequency of these events and the relevant exposure especially for larger banks to brown industries, climate considerations and prudential policies addressed in the stress test should be constantly updated, and the same climate stress should be led with higher frequency. The action of central banks, financial supervisor and government is necessary to systemically address climate change and climate related financial risks. The achievement of better performance should not be the only reason for ESG investing. ESG strategies should be valued for the potential positive impact on the environment or society. Previous literature has provided interesting evidence to address this issue through the ESG momentum strategy, which consists of overweighting those stocks that have improved their ESG rating (Nagy et al., 2016; Bos-Nehles & Veenendaal, 2019; Kaiser & Schaller, 2019). Moreover, the European Central Bank (ECB), could be strengthen its action adopting the principle of double materiality recently incorporated within the Corporate Sustainability Reporting Directive (CSRD) and using the European Financial Reporting Advisory Group standards . Further, banks with higher exposure on brown industries or involved in more controversial issues could more strictly overseen. So, in this context the study claims to Central banks and financial authorities' effective action to sensitize and above all attract interests by investors accelerating the investments in economy transition and above all safeguarding the environment and financial stability over the long run. The remainder of the paper is organised as follows. In Section 2, I discuss the literature review. Section 3 introduce data and methodology including climate risk measure and specific variables used in this paper. Section 4 reports the main results. Section 5 concludes and draws some policy implications.

2 Literature review

Empirical studies of climate risk assessment of financial actors' and markets' reaction to climate change are relevantly increased over the time as climate-related risks have become a major concern for financial regulators and a significant threat to financial stability (Chabot & Bertrand, 2023). Over the last decade the academic literature has tried to analyse the link between climate risk and financial stability and the potential adverse effects of climate change (Seneviratne et al., 2018). In this context, one of the main challenges has been represented by the lack of standardised information on the climate relevant characteristics of firms and financial products and the difficulty in identifying low-carbon and high-carbon assets. Moreover, the confusion among Environmental, Social and Governance (ESG) indices across financial data providers (Berg et al., 2022) is likely to affect the consistency of results. Nevertheless, whereas climate risk is even more considered as systemic risk, main issues seem to arise from the measurement and forecasting of climate-related and environmental risks' impact. However, despite others financial risk metrics (i.e. value-at-risk), climate risk cannot be assessed based on past events, since they are not reliable predictors of the future in this respect (Roncoroni et al., 2021). From a broad perspective, studies on climate risk have been concerned on one hand on the analysis of the macroeconomic impact of climate change, and on the other hand about the link between climate-related risk and financial stability. A first strand of literature focused on the physical effects of climate change on the whole economy (Noy, 2009; Burke et al., 2015; Hsiang et al., 2017; Diffenbaugh & Burke, 2019; Hallegatte & Engle, 2019). While concerns among the relationship between climate-related risk and financial stability have received growing attention from scholars only in the last decade, even because historical series do witness a substantial stability of climate data till 1980. The first research area is based on a careful consideration of the nature of climate risk. Among the main considerations of climate risk nature, Battiston (2021) outlined three main issues. Firstly, climate risk is "systemic and non-linear" (Battiston et al., 2017; Monasterolo, 2020; Dafermos & Nikolaidi, 2021) and if it is not timely addressed, it can lead to tipping points in the ecosystem (Galaz et al., 2018; Lenton et al., 2019). Battiston et al. (2017) outlined that direct and indirect exposures to climate-policy-relevant sectors represent a portion of banks' loan portfolios comparable to their capital. Specifically, they carried out a network-based climate stress-test on a sample of top 50 largest UE banks highlighting that the implementation of climate mitigation policies is key, both in terms of timing and expectations. Briefly, they point out that if climate policies are implemented early on and in a stable and credible framework, market participants are able to smoothly anticipate the effects. Contrarily, if the implementation is uncertain, delayed and sudden, market participants would not be able to fully anticipate the impact of policies. So, the large direct and indirect exposures of financial actors to climate-policy-relevant sectors, this might entail a systemic risk due to the price adjustments are abrupt and portfolio losses from the fossil-fuel sector and fossil-based utilities do not have the time to be compensated by the increase in value of renewable-based utilities. Second, climate risk is "endogenous", it means that worst-case scenarios depend on the perception of risk of the agents involved and their reaction to this perception (Battiston, 2019). Moreover, climate risk involves and affects through different channels several dimensions both the food-water-energy nexus and socio-economic activities related to that, increasing the "complexity of impacts and policy reactions" (Howarth & Monasterolo, 2016). This second stream of literature instead seems to be characterised by research gaps in two key areas. The first one, is represented by the lack of quantitative assessment of the impact of climate physical and transition risks on the macro-economy and the financial system, considering feedback loops and drivers of amplification. The second one concerns the internalisation of information about climate change in financial valuation and portfolio risk management (Battiston et al., 2021). In the light of the increasing attention on this issue, a lot of scholars have recently dedicated their attention to the link between the climate risks and financial stability trying to cover several research questions such as the impact of climate transition policies on financial stability, the physical risks of climate change for the financial system, and the implications of climate change for pricing in financial markets. Dafermos and Nikolaidi (2021) and Dunz et al. (2021) show that carbon tax policies need to be ac-companied by governments' "carbon tax revenue recycling" (i.e. the reinvestment of carbon tax revenues) in order to minimise the adverse distributional and financial effects of carbon pricing. For the purpose of their study, Dunz et al. (2021) incorporate banks' climate sentiments (i.e. financial actors' expectations on the impact of climate policies on firms' performance) which revising their lending strategy and firms' cost of capital as a consequence of their assessment of firms 'exposure to climate risks. They provide evidence that banks are able to mitigate the impact of the energy transition on financial stability as they anticipate the increase in the carbon tax. More recently. focusing on European financial institutions that publish Scope 3 emissions, Chabot and Bertrand (2023) have showed that that transition risk measured as Scope 1 and 2 has a limited influence on financial stability as financial institutions are low GHG emitters. While most of their transition risk depends on the GHG emissions of the companies they finance, which fall within the Scope 3 of banks. However, given the low number of companies and banks that disclose Scope 3, it implies that the transition risk as currently estimated in the literature is most likely underestimated. With regard to physical risks of climate change, Lamperti et al. (2021) find that policies that relax bank capital constraints for green loans can have more relevant positive effects on physical risks as they are implemented together with credit guarantees for green loans and carbon risk adjustments in banks' credit rating. Moreover, Flori et al. (2021) by exploring the empirical interactions between commodity prices, climate-related variables and measures of financial distress in capital markets outline that climate-related variables affect financial stability through the impact that they have on commodity prices. Finally, implications of climate change for financial market's pricing are likely to consist of evidence of transition risks impact and the bond market (Agliardi & Agliardi, 2021; Fatica & Panzica, 2021). Using a sample of companies listed on the STOXX Europe Total Market Index, Alessi e al. (2021) first show that investors accept a lower compensation for holding stocks of companies that disclose environmental data and have a lower emission intensity. They further find that losses of institutional sectors in case of higher performance of carbon-intensive companies are not quantitatively large and the reallocation of portfolios towards greener assets could reduce these losses. Finally, Bressan and Romagnoli (2021) contribute to this field showing that climate and weather derivatives can be useful financial tools for hedging climate-related risks, although several challenges may arise from the pricing of the climate and weather derivatives pointing out that the mispricing of derivatives can actually increase physical risks, undermining financial stability.

3 Data and Methodology

In this section, I introduce the different steps to build our sample and detect climate risk determinants for banks. I describe how the climate risk measure, which represents the dependent variable, is formulated, and introduce the set of explanatory and control variables of the model. Finally, I summarise all variables.

3.1 Sample of analysis

I select all public and active European Banks available on LSEG®. I filter our initial sample for those entities for which the dependent variable, as well as the CRISK, is available. Then, I consider just those entities continuously listed between 2005:Q1 and 2023:Q4, leading to a sample of 79 European listed banks. In order to observe a period of analysis as long as possible, I select the year 2005 as a starting point in relation to the availability of CRISK data for all banks of the sample. The currency used for data collection is Euro, as I consider just the European context.

The Figure 11 illustrates the size of banks captured by the mean total assets (million). The trend line with a positive slope that the mean size of banks increased over the time. However, I may outline that a higher mean size occurred the beginning and at the end of the period of analysis. It significantly increases over the Great Financial Crisis and European Financial Crisis (2007-2008), and the Sovereign Debt Crisis (2011 – 2012), then it turns to a rapid decrease between 2012 and 2017. A slightly increase was registered among 2018, as a turmoil affected financial markets and worldwide economy. Finally, after a sensitive reduction, it rise again with the Pandemic Crisis of Covid19 (2020-2022) until the end of the period also affecting by geopolitical issues.

[INSERT SOMEWHERE HERE FIGURE 1]

3.2 Measuring Climate Risk via CRISK

For the purpose of our analysis, I use a dependent variable recently introducedby Jung et al. (2021) and available at the Volatility Laboratory (V-Lab) , namely CRISK. The Climate Risk (CRISK) measures by definition "the expected capital shortfall conditional on the climate stress". This measure is based on a market-based methodology and allows to assess banks' resilience to climate-related risks and study the climate-related risk exposure of large global banks, which are likely to be more affected by climate-related risks as they finance brown firms and those are mostly exposed to climate issues (especially for their size). According to Jung et al. (2021), it focuses on a particular dimension of climate risk (transition risk). Briefly, through the CRISK they try to address the following issue: "are banks sufficiently capitalized to absorb losses during stressful conditions due to heightened climate risk?" To answer this question, they take a novel approach to measuring the potential adverse effect of transition risk on banks' capitalization which develops through three different steps. The first step is to measure the climate risk factor which is considered as a proxy for transition risk. Climate risk factor is given by the stranded asset (SA) portfolio return developed by Litterman (n.d). Previous literature pointed out that find that, globally, a third of oil reserves, half of the gas reserves, and over 80% of current coal reserves should remain unused from 2010 to 2050 to meet the target of limiting global warming to 2 degrees Celsius. It means that fossil fuels would likely become "stranded assets" more quickly moving towards a less carbon environment scenario (McGlade & Ekins, 2015). Moreover, assets in the fossil fuel industries seem to be at risk of losing market value due to transition risk related to changes in renewable technology and climate policies in light of the Paris commitments (Van der Ploeg & Rezai, 2020). In this sense, Jung et al. (2021) argue that the return on a stranded asset portfolio may represent a useful proxy to reflect market expectations on future transition climate risk. Briefly, an underperformance of SA portfolio can be interpreted as an increase of the transition risk. Then, by using the dynamic conditional beta (DCB) model, in the second step they estimate the time-varying climate betas of financial institutions. Bank i's stock return is given by the following formula:

$$r_{i,t} = \beta_{i,t}^{i,t} MKT_t + \beta_{i,t}^{Climate} CF_t + \epsilon_{i,t} \tag{1}$$

Where $r_{i,t}$ is the stock return of bank i, MKT is the market return, and CF is the climate risk factor measured in the first step. Moreover, $\beta_{i,t}^{i,t} MKT$ is the market beta and $\beta_{i,t}^{Climate} CF$ is called climate beta. Climate Beta reflects banks' loan portfolio composition. It is obtained by building a panel of loan portfolio climate beta through the compute of the weighted average climate beta for each bank where the weight is the loan size and each loan is assigned the climate beta of the respective industry.

Figure 22 shows Climate Beta trend from 2007 to 2023. As illustrated that climate betas vary over time, suggesting that it is important to estimate the betas dynamically. It measures banks' loan exposure to climate risk as the sensitivity of bank stock returns on the climate factor (CF). So, according to June et al. 2023, I assume that it is higher when banks lend more to industries with high emissions (or brown industries), or in case of crisis event such the Pandemic Crisis of 2019. In fact, I remark a strong increase on average in climate beta during the Pandemic Crisis. According to Jung et al. (2021), as the fossil fuel energy prices collapsed in 2020 "brown borrowers" loans became particularly riskier with a shorter distance to default, and the banks' stock returns became more sensitive to the transition risk, thereby affecting banks' climate risk exposure. Specifically, they note that they do not identify that transition risk caused the collapse in fossil fuel energy prices in 2020; rather, they merely exploit an event in which the climate factor declined severely. However, as illustrated in Figure 22, climate betas may also have negative values, even during the Pandemic Crisis, moving in a backwards. In line with market beta, I assume that a beta less (greater) than one implies that the bank's loan will be less (more) volatile than the banks' loans of its industry.

[INSERT SOMEWHERE HERE FIGURE 2]

Finally, extending the SRISK methodology of Acharya et al. (2011), Acharya et al. (2012), and Brownlees and Engle (2017), the third step is to calculate the CRISK. According to the definition above, CRISK is calculated as:

$$CRISK_{i,t} = KD_{i,t} - (1-K)W_{i,t}(1-LRMES_{i,t}) \tag{2}$$

where D is the book value of debt, W represents the market capitalization, and $LRMES$ indicates the Long-Run Marginal Expected Shortfall as well as the expected fractional loss of the firm equity when the SA portfolio declines significantly in a six-month period. $LRMES$ is given by the following formula:

$$LRMES = 1 - exp(\beta^{Climate} log(1-\theta)) \tag{3}$$

where θ is the climate stress level and its default value is 50%, k represents the prudential capital requirement, it is the amount of capital, expressed as a share of assets, that a firm would need to weather a stress. According to $CRISK$ methodology, the capital ratio for European firms is 5.5%. According to Jung et al. (2021) CRISK measure may be decomposed in three main components. The first component is the contribution of the firm's debt to CRISK ($dDEBT = k * \Delta D$). The second component is represented by the firm's equity to CRISK ($dEQUITY = -(1-K)(1-LRMES) * \Delta W$). And the last component consists of the contribution of an increase in climate beta to CRISK ($dRISK = (1-K) * W * \Delta LRMES$). CRISK decomposition is a key tool to better understand what drives the substantial increase in CRISK over the period analysed. Figure 33 plots the trend of CRISK of the top 10 European banks over the period of analysis considering a Predicted System Capital Shortfall for a 0%

market and a is the climate stress level of 50%. So, since CRISK is a function of climate beta, the ranking of CRISKs can differ from climate beta estimates. From a general perspective, I may observe that during the Great Financial Crisis in 2007 and the European financial crisis in 2008, the CRISK measure increased as banks were undercapitalized and vulnerable to both overall market risk and climate risk. Moreover, it increases even over the Pandemic Crisis (2019-2022), whereas even banks were not undercapitalized, they were significantly vulnerable to market risk and climate risk in relation to changes in climate factor (CF).

[INSERT SOMEWHERE HERE FIGURE 3]

To analyse separately the changes in climate risk and market risk, I further consider the marginal CRISK. Following Jung et al. (2021), the marginal CRISK is defined as the difference between CRISK (with the currently selected climate stress) and non-stressed CRISK, as well as the capital shortfall under zero climate stress scenario. It can be expressed as:

$$marginalCRISK = (1 - k)W * LRMES \tag{4}$$

Jung et al. (2021) highlight that during the global financial crisis or the European financial crisis, the mCRISKs were close to zero, differentiating the latest peak in CRISK from the earlier two peaks in Figure 4. This trend is in line to Jung et al. (2021) which pointed out that the $mCRISKs$ remain high even after fossil fuel energy prices rebound to their pre-2020 level in late 2021.

3.3 Methdology

I carry out an empirical analysis to study the main determinants of Climate Risk for European listed banks. Using a panel dataset of 79 listed European banks I implement a multiple regression analysis over the period 2005:Q1 and 2023:Q4, selecting the long run series available for the analysis. The dependent variable is represented by the changes in CRISK gathered by V-LAB. Variables are all log transformed. In line with previous literature on systemic risk (Pellegrini et al., 2022a; Tobias & Brunnermeier, 2016; López-Espinosa et al., 2012) the dependent variable is considered at time (t), while the independent and control variables are all one-quarter lagged (t-1). Panel data allows to assess the key elements over time by analysing numerous data for a long run time series of the same financial institutions over the total observed population. The regression model is defined as follow:

$$lnClimaterisk_{i,t} = \alpha + \beta_1 lnClimaterisk_{i,q-1} + \beta_2 Size_{i,q-1} + \beta_3 MarketBeta_{i,q-1} + \beta_4 ClimateBeta_{i,q-1} + \beta_5 (TotalAssets/CommonEquity)_{i,q-1} + \beta_6 Tier1_{i,q-1} + \beta_7 STL_{i,q-1} + \beta_8 MB_{i,q-1} + \beta_9 (TotalLoans/TotalAssets)_{i,q-1} + \beta 10 HHI_{i,q-1} + \beta_1 1 \Delta GDP_{i,q-1} + \beta_1 2 \Delta Inflation_{i,q-1} + \gamma + \lambda + \epsilon_i$$

Where $ln_ClimateRisk$ (or ln_CRISK) is the dependent variable log transformed. The $lnClimaterisk_{i,q-1}$ is the natural logarithm of the one-quarter lagged dependent variable. $Size_{i,q-1}$ is the natural logarithm of total assets of bank i at quarter (t-1).$MarketBeta_{i,q-1}$ is the equity market beta for bank i at quarter (t-1). $ClimateBeta_{i,q-1}$ is the equity climate beta of bank i at quarter (t-1). $(TotalAssets/CommonEquity)_{i,q-1}$ is a proxy of leverage of bank i at quarter (t-1); $Tier1_{i,q-1}$ is the Capital Adequacy ratio Tier 1 for bank i at quarter (t-1). $STL_{i,q-1}$ is the Short-Term Liability as well as the relative level of short-term wholesale funding as the total short-term debt minus cash to total liabilities ratio of bank i at quarter (t-1). $MB_{i,q-1}$ is the Market To Book Value ratio of bank i at quarter (t-1). $(TotalLoans/TotalAssets)_{i,q-1}$ is a proxy of asset structure ratio introduced by the previous literature on banks' business model (Roengpitya et al., 2014; Altunbas et al., 2011). Moreover, I consider several macroeconomic variables. Specifically, I introduce the Herfindahl-Hirschman Index (HHI) which represents a proxy at sector-level of market concentration; GDP and Inflation consist respectively of the quarter changes in the Goss Domestic Product and Overall Index of Inflation for each country. Finally, I consider Time (γ) and Crisis (λ) dummies. Following Bellavite et al. (2022), Crisis dummies concern to different ranges of time (also called regimes) which capture Crisis and Post Crisis Periods. Considering our period of analysis, I consider 6 regimes including Regime 1 which covers the Subprime Crisis over the period 2007:Q3–2008:Q3; Regime 2 captures the European Great Financial Depression over the period 2008:Q4–2010:Q2;

Regime 3 covers the Sovereign Debt Crisis over the period 2010:Q3–2012:Q4; Regime 4 captures the Post Financial Crisis Period over 2013:Q1–2015:Q4; Regime 5 covers the Pandemic Crisis over the period 2019:Q1-2022:Q3; Regime 6 captures the Post Pandemic Crisis Period over the period 2022:Q4-2023:Q4.

I define three different specifications: [a] represents the baseline regression model; [b] represents the benchmark specification (a) using accounting and financial variables and Time dummies; [c] includes accounting and financial variables and Regimes; [d] considers accounting and financial variables, Time dummies and Regimes.

3.4 Descriptive statistics

Table 11 summarizes the quarterly variables for the sample. The descriptive statistics for CRISK shows a mean value of € 4.5 million with a positive skewness of 2.36. Among the control variables, as I compare the two betas, we may observe that the mean value of market beta is higher than the climate beta. Specifically, the mean values of market beta and climate beta are respectively 1.077 and 0.087. The mean Size of the banks captured by the natural logarithm of total assets is 23.8, whereas the maximum value is 28.4. The market to book value ratio varies between a minimum of 2.4 and a maximum of 8.9, showing a mean value of 4.8; and the mean level of indebtedness of the sample is 24.3, with a positive skewness of 2.545. The mean values of the Capital Adequacy Tier 1 (also known as Core Capital ratio), which measure the level of potential losses which can be absorbed by higher quality sources of capital in the occurrence of a market stress is 14.5. Moreover, the mean value of short-term liability (STL) ratio and total loans on total assets is -0.03 and 0.570. The STL measure allows to provide useful information about banks' maturity mismatch, which occurred when a company's short-term liabilities exceed its short-term assets. Finally, the concentration of the market over the period of analysis captured by the Herfindahl Index ranges from a minimum level of 0.017 to 0.388, showing a mean value of 0.091.

[INSERT SOMEWHERE HERE TABLE 1]

4 Results

In this section, I discuss and illustrate those factors which drive the climate risk, considered as source of systemic risk, for banks. Following Jung et al. (2021), I consider the prudential capital fraction k to 5.5% for European banks and the climate stress level θ to 50%. First, I report the Pearson correlation matrix of the set of variables in Table 2??. A significant correlation arises from the pairwise correlation of all variables over the period of analysis. According to the previous literature in systemic risk (Acharya, 2010; Acharya et al., 2012; Brownlees & Engle, 2017; Pellegrini et al., 2022a), I may outline a strong correlation between the dependent variable of systemic risk, as well as Climate risk, and several variables at bank level including Size and the level of indebtedness captured by the ratio between total assets and common equity. The possibility of multicollinearity among the explanatory variables is also tested using the Variance Inflation Factors (VIFs). The maximum VIF that results from any of the models is 2.04, which is far be- low the generally employed cutoff of 10.

Table 33 reports the empirical results. It is worth noticing that an increase in CRISK measure represents an increase in banks' climate risk. I consider four different specifications of the model. For each specification, I may outline separately some key variables which tend to increase the climate risk, while on the other hand some others which reduce the climate risk for banks. Specifically, as the banks' size increase of one standard deviation, the climate risk strongly increases of 4.17 (p-value < 0.001). This evidence is in line with the previous literature on systemic risk, which point out that larger banks tend to take more risk (Pellegrini et al., 2022a; Bostandzic & Weiss, 2018; Tobias & Brunnermeier, 2016; López-Espinosa et al., 2012). In the case of banks' climate risk, I assume that it is determined by larger banks exposure to industries significantly affected by environmental controversial issues and with higher carbon emissions. Among the other traditional drivers of system risk, I highlight a positive and significant impact of the level of indebtedness and market beta, which respectively contribute to an increase of the dependent level of 12.22 and 2.70 basis points with a p-value of 1%. While evidence on the relationship between systemic risk and leverage are not univocal, as I consider how the beta market affects the measure of systemic risk our findings are support by previous evidence in systemic risk literature (Pellegrini et al., 2022a). At macro level, I detect two other key variables which are likely to increase banks' climate risk including the increase in one-quarter lagged change in overall inflation (including energy and food prices) and the market concentration captured by the Herfindahl Index. More specifically, as the change in overall inflation increases of one standard deviation, the dependent variable slightly increases of 0.04 basis points (p-value$<$0.001). While higher market concentration is likely to be significantly and strongly correlated to a greater climate risk for banks in measure of 17.00 basis points (p-value$<$0.001). However, I may argue that there are also several key variables which seem to contribute to decrease climate risk for banks including the one-quarter lagged short-term liability ratio (STL), the one-quarter lagged Capital Adequacy ratio Tier 1 (TIER 1), the one-quarter lagged Climate Beta and the macroeconomic variable of GDP, as well as the one-quarter lagged change in GDP. Specifically, as the STL increase of one standard deviation, the dependent variable significantly decreases of 6.40 basis points (p-value < 0.05). STL measure allows to provide useful information about banks' maturity mismatch, which occurs when a company's short-term liabilities exceed its short-term assets. Maturity mismatch may vary across banks and in relation to business model characteristic. Maturity mismatch is a particular constraint in financing environmental projects due to the comparatively higher capital expenditure and considerable uncertainty on the future of technological innovation aimed at reducing carbon emissions (Bernal-Conesa et al., 2017; Weitzman, 2013). I argue that the mitigating role of STL on climate risk may represent a direct consequence of long-term environmental investment which rewards banks for their commitment in terms of lower climate risk exposure. Considering the Tier 1, we may observe that as it rise of one standard deviation, the Climate risk tends significantly to reduce of 4.641 basis points (p-value$<$0.10). According to the updated requirements of the European Central Bank (ECB) and European authorities the minimum level of CET1 ratio increase from 10.7% to 11.1% (Bank, 2023). The mean value of Capital Adequacy Tier 1 is higher than the minimum threshold set by the ECB (see Table 11). This finding is complementary to the previous evidence on leverage, which positive affects the dependent variable increasing banks' climate risk. Finally, the one quarter lagged increase in climate beta, which measures the sensitivity of bank stock returns on the climate factor, seems to significantly reduce climate risk of 2.90 basis points (p-value < 0.10). Jung et al. (2021) outline that climate beta reflects banks' loan exposure to climate risk, assuming that it is higher when lending more to industries with high emissions (or brown industries). So, they assume that CRISK is higher for banks that are larger, more leveraged, and with higher climate beta. However, since CRISK is a function of climate beta, as well as a function of the size and leverage of a bank, the ranking of CRISKs can differ from that of climate beta estimates, which dynamically change over the period of analysis. Moreover, if this measure, similarly to the beta of market as argued by Bellavite Pellegrini et al. (2022) may help us to understand how bank risk has evolved over time also in relation to the effects regulatory changes, I may argue that constant monitoring of climate beta may alarm banks' management turning to a decrease in CRISK measure. Finally, as the one-quarter lagged change in GDP increases of one standard deviation, climate risk decreases of 0.005 basis points.

For a sake of completeness, I briefly discuss the impact of the other variables considered in the model specification even not significant including the market to book value ratio (MB ratio) and the proxy of asset structure (total loans on total assets).Our evidence outline that the sign of MB value coefficient changes as I introduce in the specification model crisis dummies (or regimes) moving from a positive to a negative sign. Previous literature on systemic risk pointed out that this measure is in general comparatively costly and difficult to implement within a short time span, especially in periods of distress, causing asset pricing misalignments and thus increasing systemic risk (Bank, 2021). Moreover, these measures are lower for banks, due the investors concerned about a bank's hidden risk exposures. As I consider instead banks' asset structure, I may observe that an increase of one standard deviation tends to increase the climate risk for banks, however it is not significant.

[INSERT SOMEWHERE HERE TABLE 3]

5 Conclusions

This empirical study tries to expand the knowledge among the potential drivers of climate related financial risk providing new evidence within the climate finance field of literature. From a broad perspective, the sustainability path related to environmental issues for European listed banks arise from a strong commitment of European Central Bank (ECB) and financial authorities which strictly monitor banks' impact on real economy and financial stability. Although there is still a significant gap among research methodologies, the increasing importance to assess and monitor climate-related and environmental risks both for scholars and practitioners, has provided firsts interesting findings. According to the recent academic literature, climate change represents the major source of risk for the financial system (Battiston et al., 2021). For the purpose of our analysis, I consider a recent study published in academic literature by Jung et al. (2021), which introduce a measure of climate risk (CRISK) available at the Volatility Laboratory (V-Lab). The Climate Risk (CRISK) extends the SRISK methodology of Acharya et al. (2011), Acharya et al. (2012), and Brownlees and Engle (2017). It represents the expected capital shortfall conditional on the climate stress, and it is computed as the difference between the book value of debt weighted for the prudential capital ratio (k), which according to the methodology, for European financial entities is 5.5%, and (1-K) W_it (1- $LRMES_it$). Briefly, W represents the market capitalization, and LRMES indicates the Long-Run Marginal Expected Shortfall as well as the expected fractional loss of the firm equity. Note an increase in CRISK measures represents an increase in banks' climate risk. Specifically, considering the availability of CRISK information, I focus on a panel data sample of 79 European listed banks over the period 2005:Q1 - 2023:Q4 I define a set of traditional measures within the literature on systemic risk such a proxy of size and leverage, the Market to Book Value, the Market beta, the Short-term liability ratio (Pellegrini et al., 2022a; Tobias & Brunnermeier, 2016; López-Espinosa et al., 2012). Moreover, I consider the measure of Capital Adequacy Tier 1 (%), the ratio between Total Loans and Total Assets as a proxy of assets structure (Roengpitya et al., 2014; Altunbas et al., 2011) and the climate beta, which assess the sensitivity of bank stock returns on the climate factor. Further, I consider three macroeconomic measures at country level such the quarterly change in both the Gross Domestic Product and Overall Inflation (including energy and food prices). Finally, I include the Herfindahl-Hirschman Index (HHI) which represents a proxy of a market concentration. In order to eliminate potential bias, I implement both Time dummies, for each year of the period analysed, and Crisis dummies (also called regimes). Following

Bellavite et al. (2022) I consider 6 regimes including Regime 1 which covers the Subprime Crisis over the period 2007:Q3–2008:Q3; Regime 2 captures the European Great Financial Depression over the period 2008:Q4–2010:Q2; Regime 3 covers the Sovereign Debt Crisis over the period 2010:Q3–2012:Q4; Regime 4 captures the Post Financial Crisis Period over 2013:Q1–2015:Q4; Regime 5 covers the Pandemic Crisis over the period 2019:Q1-2022:Q3; Regime 6 captures the Post Pandemic Crisis Period over the period 2022:Q4-2023:Q4. Table 33 shows empirical results for the baseline model (a), the baseline model with only Time dummies (b) and only regimes (c), while the last specification (d) considers both Time dummies and Crisis dummies. Focus on this last specification I may observe that an increase in the banks' size strongly increases the climate risk of 4.17 (p-value < 0.001). As pointed out by the previous literature on systemic risk, larger banks are willing to be more risky especially for their size (Pellegrini et al., 2022b; Tobias & Brunnermeier, 2016; ?, ?). Moreover, larger banks show also a greater exposure to "brown" industries or firms significantly affected by environmental controversial issues. Further, I outline a positive and significant impact of the level of indebtedness, where the rise of one standard deviation of the ratio between total assets and common equity, tends to increase the CRISK of 12.22 basis points (p-value < 0.001); while an increase in market beta, contributes to an increase of the dependent level of 2.70 basis points with a p-value of 1%. While evidence on the relationship between systemic risk and leverage are not univocal, as we consider how the beta market affect the measure of systemic risk our findings are supported by previous evidence in systemic risk literature (Pellegrini et al., 2022a). Among macroeconomic variables, I outline two other drivers of climate risk such the increase in one-quarter lagged change in overall inflation (including energy and food prices) and the proxy of market concentration as well as the Herfindahl Index, which respectively contribute to an increase in the dependent variable of 0.04 basis points and 17.00 basis points (p-value$<$0.001). Nevertheless, findings highlight that the rise of one standard deviation in the one-quarter lagged short-term liability ratio (STL) and the one-quarter lagged Capital Adequacy ratio Tier 1 (TIER 1), significantly decreases climate risk for banks of 6.40 basis points (p-value < 0.05) and 4.641 (p-value < 0.10) respectively. Previous literature in this field pointed out that the maturity mismatch is a particular constraint in financing environmental projects due to the comparatively higher capital expenditure and considerable uncertainty on the future of technological innovation aimed at reducing carbon emissions(Bernal-Conesa et al., 2017; Weitzman, 2013). So, I argue that the mitigating role of STL on climate risk may represent a direct consequence of long-term environmental investment which rewards banks for their commitment in terms of lower climate risk exposure. With regard to the relationship between Tier 1 and Climate Risk, I outline the complementary evidence with previous impact of the leverage on climate risk. It is not surprising, as I consider that the mean value of Capital Adequacy Tier 1 of our sample seems to be higher than the updated requirements of the European Central Bank (ECB) and European authorities the minimum level of CET1 ratio increase of 11.1% (see Table 21). Moreover, the one-quarter lagged increase in Climate Beta, tends to significantly reduce the dependent variable of 2.90 basis points (p-value < 0.10). Jung et al. (2021) assumes that CRISK is higher for banks that are larger, more leveraged, and with higher climate beta. However, as I compare the trends over the time of CRISK and climate beta estimates, I may show that significantly differ between them. Climate betas dynamically change over the period of analysis (see Figure 3**??**) and may provide as market beta useful elements to assess whether bank risk has evolved over time also in relation to the effects regulatory changes. So, I explain the moderating role of climate beta as a consequence of the monitoring by banks' management. Specifically, as the one-quarter lagged Climate beta rise of one standard deviation, the climate risk significantly reduces of 2.90 basis points (p-value < 0.10). Finally, as the one-quarter lagged change in GDP increases of one standard deviation, climate risk decreases of 0.005 basis points. The R2 (within) is higher than 40% for each specification of the model, showing the grata capability of the selected variables to explain changes in the dependent variable. To strength the robustness of the estimation I control for heteroskedasticity using the robust standard errors and FE estimation according to the result of Hausman test.

This study contributes to the existing literature providing empirical evidence on the different drivers of climate risk for European listed banks. Specifically, our results support policy makers in the design of climate-related financial risks strategies, pointing out the key variables which are likely to contribute to an increase in climate risk and, on the other hand, those contribute to reduce it. Further, I outline the relevance to constantly monitor the dynamical changes over the period of climate betas, to assess the measure in which they can affect banks' stability and the whole financial stability as an extreme environmental event occurred. Differences in CRISK may arise from inequality in terms of wealth among across different countries. Given the increasing frequency of these events and the relevant exposure especially for larger banks to brown industries, climate considerations and prudential policies addressed in the stress test should be constantly updated, and the same climate stress should be led with higher frequency. Moreover, whereas forecasting potential climate-related risks impact is even more relevant, providing historical data could be crucial to form the adequate knowledge to challenge climate issues. So, in this context, effective actions to sensitize and attract interests by investors by central banks, financial supervisor and government may be crucial to accelerate investments in economy transition stability over the long run. So, what can make a significant change? The achievement of better performance should not be the only reason for ESG investing. ESG strategies should be valued for the potential positive impact on the environment or economic society. Among the main previous evidence to support this approach, I outline the use of ESG momentum, which consists of overweighting those stocks that have improved their ESG rating (Nagy et al., 2016; Bos-Nehles & Veenendaal, 2019; Kaiser & Schaller, 2019). Moreover, the European Central Bank (ECB) could be strengthening its action adopting the principle of double materiality incorporated within the Corporate Sustainability Reporting Directive (CSRD) adopting the European Financial Reporting Advisory Group standards. Furtherly, more strictly Capital Adequacy Tier 1 or mandatory disclosure on Scope 3 for those institutions with higher exposure to brown industries should be asked by ECB.

To conclude, this study provides several insights for the future research. Firstly, this study analyses just the banking sector, however given the higher exposure to fossil-fuel companies of funds and insurance (Weyzig et al., 2014), and previous evidence in systemic risk literature (Pellegrini et al., 2022a, 2022b), extending the analysis on other financial entities, shadow banking entities included, may provide interesting results. Further evidence also considering the marginal CRISK as dependent variable may be provided to cluster climate drivers to financial drivers. Moreover, extending the set of variables at country level considering indexes of inequality wealth, corruption and even proxy of culture. Finally, the presence of negative climate betas over the Pandemic Crisis, could therefore open a reflection on feasible hedging strategy portfolio.

References

Acharya, V. V. (2010). Regulating wall street: The dodd-frank act and the new architecture of global finance. *(No Title)*.

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2012). How to calculate systemic risk surcharges. *Quantifying systemic risk*, 175–212.

Agliardi, E., & Agliardi, R. (2021). Pricing climate-related risks in the bond market. *Journal of Financial Stability*, *54*, 100868.

Alessi, L., Di Girolamo, E. F., Pagano, A., & Giudici, M. P. (2024). Accounting for climate transition risk in banks' capital requirements. *Journal of Financial Stability*, 101269.

Allen, T., Dees, S., Caicedo Graciano, C. M., Chouard, V., Clerc, L., de Gaye, A., … others (2020). Climate-related scenarios for financial stability assessment: An application to france. –.

Altunbas, Y., Marqués-Ibánez, D., & Manganelli, S. (2011). Bank risk during the financial crisis: do business models matter? –.

Bank, E. C. (2020). Guide on climate-related and environmental risks–supervisory expectations relating to risk management and disclosure. –.

Bank, E. C. (2021). Ecb economy-wide climate stress test. –.

Bank, E. C. (2023). 2023 stress test of euro area banks final results. –.

Bank, E. C. (2024). Climate-related financial disclosures of the ecb's non-monetary policy portfolios. *available at https://www.ecb.europa.eu/ecb/climate/climate-related-financial-disclosures/shared/pdf/ecb.crfd2024$_N$MPPs.en.pdf*.

Battiston, S. (2019). The importance of being forward-looking: managing financial stability in the face of climate risk. Financial Stability Review*(23), 39–48.*

Battiston, S., Dafermos, Y., & Monasterolo, I. (2021). Climate risks and financial stability. Journal of Financial Stability*, 54, 100867.*

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. Nature Climate Change*, 7(4), 283–288.*

Berg, F., Koelbel, J. F., & Rigobon, R. (2022). Aggregate confusion:the divergence of ESG ratings. Review of Finance*, 26(6), 1315–1344.*

Bernal-Conesa, J. A., de Nieves Nieto, C., & Briones-Peñalver, A. J. (2017). Csr strategy in technology companies: Its influence on performance, competitiveness and sustainability. Corporate social responsibility and environmental management*, 24(2), 96–107.*

Bolton, P., Despres, M., Da Silva, L. A. P., Samama, F., & Svartzman, R. (2020). The green swan. BIS Books*.*

Bos-Nehles, A. C., & Veenendaal, A. A. (2019). Perceptions of hr practices and innovative work behavior: the moderating effect of an innovative climate. The International Journal of Human Resource Management*, 30(18), 2661–2683.*

Bostandzic, D., & Weiss, G. N. (2018). Why do some banks contribute more to global systemic risk? Journal of Financial Intermediation*, 35, 17–40.*

Bressan, G. M., & Romagnoli, S. (2021). Climate risks and weather derivatives: A copula-based pricing model. Journal of Financial Stability*, 54, 100877.*

Brownlees, C., & Engle, R. F. (2017). Srisk: A conditional capital shortfall measure of systemic risk. The Review of Financial Studies*, 30(1), 48–79.*

Burke, M., Dykema, J., Lobell, D. B., Miguel, E., & Satyanath, S. (2015). Incorporating climate uncertainty into estimates of climate change impacts. Review of Economics and Statistics*, 97(2), 461–471.*

Carney, M. (2015). Breaking the tragedy of the horizon–climate change and financial stability. Speech given at Lloyd's of London*,* 29*, 220–230.*

Chabot, M., & Bertrand, J.-L. (2023). Climate risks and financial stability: Evidence from the european financial system. Journal of Financial Stability*,* 69*, 101190.*

Dafermos, Y., & Nikolaidi, M. (2021). How can green differentiated capital requirements affect climate risks? a dynamic macrofinancial analysis. Journal of Financial Stability*,* 54*, 100871.*

Diffenbaugh, N. S., & Burke, M. (2019). Global warming has increased global economic inequality. Proceedings of the National Academy of Sciences*,* 116*(20), 9808–9813.*

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*, 100872.*

Fatica, S., & Panzica, R. (2021). Green bonds as a tool against climate change? Business Strategy and the Environment*,* 30*(5), 2688–2701.*

Flori, A., Pammolli, F., & Spelta, A. (2021). Commodity prices co-movements and financial stability: A multidimensional visibility nexus with climate conditions. Journal of Financial Stability*,* 54*, 100876.*

Galaz, V., Crona, B., Dauriach, A., Scholtens, B., & Steffen, W. (2018). Finance and the earth system–exploring the links between financial actors and non-linear changes in the climate system. Global Environmental Change*,* 53*, 296–302.*

Hallegatte, S., & Engle, N. L. (2019). The search for the perfect indicator: Reflections on monitoring and evaluation of resilience for improved climate risk management. Climate Risk Management*,* 23*, 1–6.*

Howarth, C., & Monasterolo, I. (2016). Understanding barriers to decision making in the uk energy-food-water nexus: The added value of interdisciplinary approaches. Environmental Science & Policy*,* 61*, 53–60.*

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., . . . others (2017). Estimating economic damage from climate change in the united states. Science*,* 356*(6345), 1362–1369.*

Jung, H., Engle, R. F., & Berner, R. (2021). Crisk: measuring the climate risk exposure of the financial system. FRB of New York Staff Report*(977).*

Kaiser, L., & Schaller, F. (2019). Environmentally (un-) friendly portfolio construction. Journal of Investment Consulting*,* 19*(1), 43–52.*

Lamperti, F., Bosetti, V., Roventini, A., Tavoni, M., & Treibich, T. (2021). Three green financial policies to address climate risks. Journal of Financial Stability*,* 54*, 100875.*

Lenton, T. M., Rockström, J., Gaffney, O., Rahmstorf, S., Richardson, K., Steffen, W., & Schellnhuber, H. J. (2019). Climate tipping points—too risky to bet against. Nature*,* 575*(7784), 592–595.*

López-Espinosa, G., Moreno, A., Rubia, A., & Valderrama, L. (2012). Short-term wholesale funding and systemic risk: A global covar approach. Journal of Banking & Finance*,* 36*(12), 3150–3162.*

McGlade, C., & Ekins, P. (2015). The geographical distribution of fossil fuels unused when limiting global warming to 2 c. Nature*,* 517*(7533), 187–190.*

Monasterolo, I. (2020). Climate change and the financial system. Annual Review of Resource Economics*,* 12*(1), 299–320.*

Nagy, Z., Kassam, A., & Lee, L.-E. (2016). Can esg add alpha? an analysis of esg tilt and momentum strategies. The Journal of Investing*,* 25*(2), 113–124.*

NGFS, N. (2021). Climate scenarios for central banks and supervisors. –.

Noy, I. (2009). The macroeconomic consequences of disasters. Journal of Development economics, 88*(2), 221–231.*

of England, B. (2018). Bank of england (2018). transition in thinking: The impact of climate change on the uk banking sector. –.

Pellegrini, C. B., Cincinelli, P., Meoli, M., & Urga, G. (2022a). The contribution of (shadow) banks and real estate to systemic risk in china. Journal of Financial Stability, 60*, 101018.*

Pellegrini, C. B., Cincinelli, P., Meoli, M., & Urga, G. (2022b). The role of shadow banking in systemic risk in the european financial system. Journal of Banking & Finance, 138*, 106422.*

Roengpitya, R., Tarashev, N. A., & Tsatsaronis, K. (2014). Bank business models. BIS quarterly review December.

Roncoroni, A., Battiston, S., D'Errico, M., Hałaj, G., & Kok, C. (2021). Interconnected banks and systemically important exposures. Journal of Economic Dynamics and Control, 133*, 104266.*

Seneviratne, S. I., Rogelj, J., Séférian, R., Wartenburger, R., Allen, M. R., Cain, M., ... others (2018). The many possible climates from the paris agreement's aim of 1.5 c warming. Nature, 558*(7708), 41–49.*

Tobias, A., & Brunnermeier, M. K. (2016). Covar. The American Economic Review, 106*(7), 1705.*

Van der Ploeg, F., & Rezai, A. (2020). Stranded assets in the transition to a carbon-free economy. Annual review of resource economics, 12*(1), 281–298.*

Weitzman, M. L. (2013). Tail-hedge discounting and the social cost of carbon. Journal of Economic Literature, 51*(3), 873–882.*

Weyzig, F., Kuepper, B., van Gelder, J. W., & van Tilburg, R. (2014). The price of doing too little too late. The impact of the carbon bubble on the EU financial system, Green European Foundation, Brussels.

APPENDIX

Table 1: Descriptive Statistics

Variables	**Mean**	**Median**	**Std.Dev.**	**Max**	**Min**	**Skewness**
Climate risk (mln)	4,531	-101.75	17,850	80,797	-35,037	-2.36
Market Beta	1.077	1.009	0.614	3.191	-.071	.853
Climate Beta	.087	.069	0.306	1.077	-.785	.29
Size (ln)	23.796	24.393	4.934	28.421	0.201	-3.786
Total Assets/Common Equity	24.26	16.217	24.449	145.298	1.378	2.545
Tier 1(%)	14.497	14	4.641	32.18	5.83	815
STL	-.03	-.041	0.129	.537	-.322	1.885
Total loans/ Total Assets	.57	.601	0.192	1.08	.004	-.649
MB ratio	4.791	4.713	1.031	8.864	2.392	1.02
HHI (ln)	-2.602	-2.688	0.632	-1.056	-3.958	.277
ΔGDP	-.256	-.061	1.189	.200	-.600	-3.046
$\Delta Inflation$	0.063	0.00	.486	.350	-.75	4.984

The Table reports the descriptive statistics for the following variables: $ClimateRisk$ is the dependent variable. $MarketBeta$ is the equity market beta for bank i. $ClimateBeta$ is the equity climate beta of bank i, $Size$ is the natural logarithm of total assets of bank i. $(TotalAssets/CommonEquity)$ is a proxy of leverage; $Tier1$ is the Capital Adequacy ratio Tier 1; STL is the Short-Term Liability as well as the relative level of short-term wholesale funding as the total short-term debt minus cash to total liabilities ratio, MB is the Market To Book Value ratio and $(TotalLoans/TotalAssets)$ is a proxy of asset structure ratio introduced by the previous literature on banks' business model (Roengpitya et al., 2014; Altunbas et al., 2011). further, I consider several macroeconomic variables including the Herfindahl-Hirschman Index (HHI) which represents a proxy at sector-level of market concentration, and ΔGDP and $\Delta Inflation$ which consist respectively of the changes in the Goss Domestic Product and Overall Index of Inflation for each country.

Table 2: Matrix correlation.

Matrix Correlation	**Climate risk**	**Market Beta**	**Climate Beta**	**Size**	**Tot. Assets/Common Equity**	**STL**	**Total loans/ Total Assets**	**MB ratio**	**HHI**	**Tier1**	ΔGDP	$\Delta Inflation$
Climate risk	1											
Market Beta	0.259*	1										
Climate Beta	0.149*	-0.056*	1									
Size	0.382*	0.330*	-0.046*	1								
Tot. Assets/Common Equity	0.521*	0.337*	0.089*	0.287*	1							
STL	0.002	-0.035	-0.164*	-0.079*	-0.017	1						
Total loans/ Total Assets	-0.299*	-0.149*	0.016	-0.183*	-0.044*	-0.057*	1					
MB ratio	-0.003	0.065*	0.045*	-0.088*	0.142*	-0.70*	0.009	1				
HHI	-0.161*	-0.056*	0.145*	0.036*	-0.065*	-0.062*	0.010	0.180*	1			
Tier1	-0.010	-0.013	0.146*	-0.084*	-0.115*	-0.101*	0.195*	0.078*	0.120*	1		
ΔGDP	-0.033*	-0.024	-0.018	-0.030*	-0.034*	0.063*	-0.012	0.007	-0.027*	-0.024	1	
$\Delta Inflation$	-0.013	0.063*	-0.046*	-0.024	-0.033*	0.010	0.009	-0.016	-0.016	-0.049*	0.000	1

bottomrule

The Table reports the correlations for dependent and independent variables: $ClimateRisk$ is the dependent variable. $MarketBeta$ is the equity market beta for bank i. $ClimateBeta$ is the equity climate beta of bank i, $Size$ is the natural logarithm of total assets of bank i. $(TotalAssets/CommonEquity)$ is a proxy of leverage; $Tier1$ is the Capital Adequacy ratio Tier 1; STL is the Short-Term Liability as well as the relative level of short-term wholesale funding as the total short-term debt minus cash to total liabilities ratio, MB is the Market To Book Value ratio and $(TotalLoans/TotalAssets)$ is a proxy of asset structure ratio introduced by the previous literature on banks' business model (Roengpitya et al., 2014; Altunbas et al., 2011). further, I consider several macroeconomic variables including the Herfindahl-Hirschman Index (HHI) which represents a proxy at sector-level of market concentration, and ΔGDP and $\Delta Inflation$ which consist respectively of the changes in the Goss Domestic Product and Overall Index of Inflation for each country. VIF is the Variance Inflation Factor and is used to detect collinearity of the regressors. denotes the statistical significance at 5% level.

Table 3: Empirical results

Dependent variable: lnCRISK	**[i]**	**[ii]**	**[iii]**	**[iv]**
$lnCRISK_{i,q-1}$	.353***	.334***	.343***	.334***
	(.036)	(.036)	(.034)	(.036)
$MarketBeta_{i,q-1}$	.036	.059**	.045*	.044**
	(.024)	(.026)	(.023)	(.026)
$ClimateBeta_{i,q-1}$	-.105**	-.134**	-.157***	-.095*
	(.047)	(.053)	(.046)	(.052)
$Size_{i,q-1}$	.855***	.854***	.869	.846***
	(.089)	(.087)	(.095)	(.087)
$TotalAssets/CommonEquity_{i,q-1}$	.006***	.005***	.005***	.005***
	(.001)	(.001)	(.001)	(.001)
$STL_{i,q-1}$	-.496*	-.417	-.471	-.408
	(.282)	(.266)	(.284)	(.262)
$MB_{i,q-1}$	.032**	-.006	.014	-.004
	(.037)	.(.03)	(.036)	(0.029)
$Tier1_{i,q-1}$	-.008**	-.011**	.005	-0.01**
	(.003)	(.005)	(.004)	(.004)
$HHI_{i,q-1}$	.239**	.265**	.278***	.269**
	(.101)	(.119)	(.102)	(0.118)
$TotalLoans/TotalAssets_{i,q-1}$	.07	.074	.073	.071
	(.064)	(.062)	(.068)	(0.061)
$\Delta GDP_{i,q-1}$	-.0001*	-.0007	-.000001	-.000001
	(.0005)	(.0004)	(.0004)	(.0001)
$\Delta Inflation_{i,q-1}$	-.0001	-.0002**	-.0002**	-.0003**
	(.0001)	(.0001)	(.0001)	(.0001)
Constant	-15.867***	-10.842***	-16.023***	-13.303***
	(2.144)	(2.121)	(2.366))	(1.23)
Banks fixed effects	YES	YES	YES	YES
Time dummies	NO	YES	NO	YES
Crisis dummies (Regimes)	NO	NO	YES	YES
N. Obs.	1,843	1,843	1,843	1,843
R^2 *within*	0.4362	0.4683	0.4500	0.4775

The table reports regressions using alternative specifications. The dependent variable is CRISK. $Size_{i,q-1}$ is the total assets of bank i at quarter (t-1); $TotalAssets/TotalEquity_{i,q-1}$ of bank i at quarter is a proxy of leverage (t-1); $MB_{i,q-1}$ is the Market To Book Value ratio of bank i at quarter (t-1); $STL_{i,q-1}$ is the Short-Term Liability ratio which captures the relative level of short-term wholesale funding as the total short-term debt minus cash to total liabilities ratio (or Maturity Mismatch) of bank i at quarter (t-1); $MarketBeta_{i,q-1}$ is the equity market beta for bank i at quarter (t-1); $ClimateBeta_{i,q-1}$, is the climate beta for bank i at quarter (t-1). $Tier1_{i,q-1}$ is the Capital Adequacy ratio Tier 1 for bank i at quarter (t-1); $TotalLoans/TotalAssets_{i,q-1}$ is a proxy of asset structure for bank i at quarter (t-1); $HHI_{i,q-1}$ is the Herfindahl Index for bank bank i at quarter (t-1) and it represents a country level measure used as a proxy of market concentration; $\Delta GDP_{i,q-1}$ is the change in Gross Domestic Product at country level for bank i at quarter (t-1) and $\Delta Inflation_{i,q-1}$is the change in overall inflation (including energy and food prices for bank i at quarter (t-1). Regime 1 which covers the Subprime Crisis over the period 2007:Q3–2008:Q3; Regime 2 captures the European Great Financial Depression over the period 2008:Q4–2010:Q2; Regime 3 covers the Sovereign Debt Crisis over the period 2010:Q3–2012:Q4; Regime 4 captures the Post Financial Crisis Period over 2013:Q1–2015:Q4; Regime 5 covers the Pandemic Crisis over the period 2019:Q1-2022:Q3; Regime 6 captures the Post Pandemic Crisis Period over the period 2022:Q4-2023:Q4. Roust standard errors are reported in brackets. Sample period: 2005:1–2023:4. , , denote the 10%, 5% and 1% significance

Figure 1: Climate Beta fluctuations 2005:Q1 and 2023:Q4

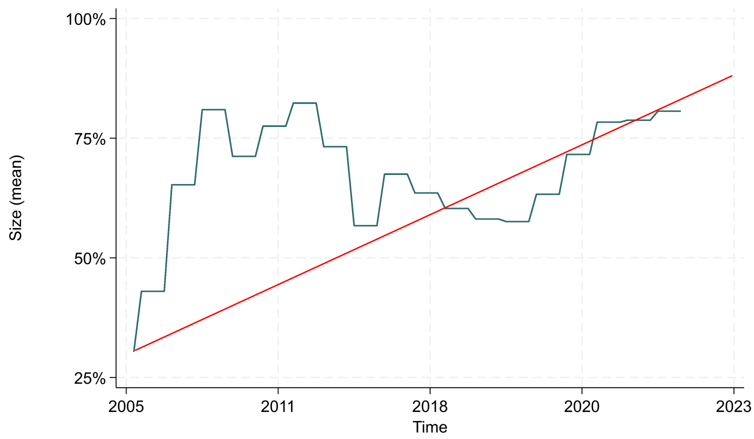

Figure 2: Banks Size between 2005:Q1 and 2023:Q4

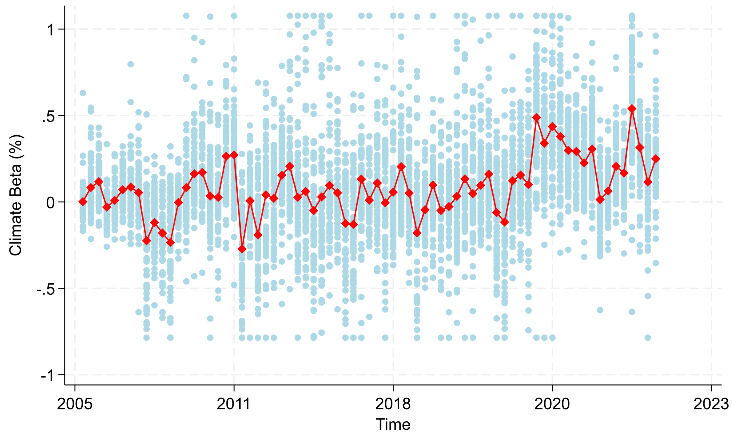

Figure 3: Climate Risk 2005:Q1 and 2023:Q4 (Top 10 EU banks)