



Climate risks and financial stability: Evidence from the European financial system

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ABSTRACT

Climate-related risks have become a major concern for financial regulators and can pose a significant threat to financial stability. In this paper, we first propose a theoretical framework for the transmission of climate risks to financial institutions and the financial system. We then estimate the influence of physical and transition risks on the European financial system through bank-level and system-wide measures of financial stability. We find that Scope 3 greenhouse gas emissions, chronic and acute climate risks negatively affect financial stability at both the financial institution and system levels. Temperature anomalies, heat waves, wildfires and droughts are among the most significant risks. As Europe warms twice as fast as the rest of the world, our theoretical and empirical results urge regulators to mandatorily require the assessment and disclosure of corporate climate risks to allow banks to adjust their prudential capital requirements.

1. Introduction

Climate change is one of the most important challenges facing the world's economies in the coming decades (WEF, 2022; Ranger et al., 2022). The conclusions of the sixth Intergovernmental Panel on Climate Change report (IPCC, 2021) are unequivocal: climate change is global, rapid and intensifying. The speed at which the climate is changing is unprecedented in thousands of years. Human activities and greenhouse gas (GHG) emissions in particular are causing an increase in the Earth's average surface temperature, which in turn leads to increased climate variability and more frequent and intense extreme climate events. Europe is particularly exposed as temperature is rising twice as fast as in the rest of the world.¹

The transition away from fossil fuels, whether driven by compelling climate policies, technology, or consumer preferences, creates opportunities for some industries. Transition however poses significant risks for the many other industries that depend on fossil fuels, causing potential losses in profits and value for the companies involved and the banks that finance them. The Financial Stability Board (FSB) was tasked with clarifying the short- and long-term risks to financial stability and considering measures to mitigate them. Three risk categories were proposed by Carney (2015): transition, physical, and liability risks. Transition risk refers to the financial risks posed by the implementation of climate policies and regulations, both directly on high-emitting companies and indirectly on their lenders and investors. Physical risk is the

financial impact on economic activity and financial assets of a changing climate, which includes both gradual changes in weather patterns and climate variability (termed “chronic”), and extreme weather events (termed “acute”). 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 (Batten et al., 2016; Monasterolo, 2020; ECB, 2020; BIS, 2021; NGFS, 2020).

A significant body of literature has been developed by both academics and regulators to investigate these risks and their consequences on the financial system. Research has initially focused on transition risk (Bressan and Romagnoli, 2021). The measurement of transition risk as it applies to financial institutions is largely based on the level of GHG emissions associated to bank lending. Ehlers et al. (2022) find that despite material risks faced by some borrowers, the overall carbon footprint, including indirect emissions, does not seem to be fully priced. Kacperczyk and Peydró (2021) and Reghezza et al. (2021) observe that firms with high emissions receive less bank credit and have to reduce their investments. In addition, a rapidly growing body of literature based on stress tests and IPCC GHG emission scenarios highlights the potential materiality of transition risk for the financial system (Battiston et al., 2017; Vermeulen et al., 2019; Reinders et al., 2020; NGFS, 2019; Allen et al., 2020; Roncoroni et al., 2021). However,

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¹ Temperatures in Europe increase more than twice global average. WMO (2022). Press release No. 02112022.

the amount of GHGs already emitted will remain in the atmosphere for decades. Hence, the benefits of climate policies, technological improvements or consumer preferences in terms of risk reduction will not have positive effects on climate for some time to come. Meanwhile, companies must adapt to the consequences of rapidly increasing climate variability, and banks that finance them must plan to adapt their capital adequacy. Thus, a second body of literature focused on the influence of physical risks is emerging (Caloia and Jansen, 2022). Klomp (2017) and Mallucci (2020) explore the influence of natural disasters on bank lending. Huang et al. (2018) find that the probability of losses due to major storms, floods, and heat waves is associated with lower and more volatile corporate profits and cash flows.

Physical risks are progressively integrated into the methodologies for analyzing the impact on financial stability (BIS, 2021; Bavandi et al., 2022). In Europe, the European Central Bank (ECB) carried out a first EU economy-wide climate risk stress test on 4 millions corporates and 1600 consolidated banking groups that includes three physical risks, namely floods, wildfires, and sea-level rise (Alogoskoufis et al., 2021). The expected losses by hazard type projected to 2050 showed that wildfires and floods have the potential to destroy physical capital. The study emphasizes wildfires as the most widespread events affecting a wider geographical area than floods. Yet, 41 years of empirical extreme events evidence (1980–2020) show that hydrological events (floods) accounted for 44% of total economic losses, meteorological events (storms) for 34%, and climatological events (heat waves, cold waves, droughts and wildfires) for only 14% altogether (European Environment Agency, 2022). This difference is likely due to a lack of knowledge of the exact location of assets at risk. The approach used by the ECB relied on banks providing the location of corporate clients' exposures, to which the ECB applied backward-looking and forward-looking climate data. Information related to the location and value of each asset at risk is not accessible to banks as it is not disclosed in annual reports. For lack of a better alternative, the location they provided to the ECB was in most cases the address of the head office associated to the loan documentation, not that of the production assets, warehouses, or key suppliers, and distribution networks exposed to climate risks. Hence, measurement of physical risks on the European financial system was likely biased.

In response to the lack of climate-related disclosures, the FSB established the Task Force on Climate-related Financial Disclosures (TCFD). Its main mission was to develop a set of voluntary and consistent recommendations on the information that companies should provide to investors, lenders and insurance underwriters on their climate-related financial risks. The initial reporting framework was launched in 2017 (TCFD, 2021). The 2021 status report shows that climate-related financial reporting is building momentum, with 2,600 organizations having adopted the TCFD framework, including 1,069 financial institutions responsible for \$194 trillion in assets. In Europe, climate risk reporting, in conformity with the Corporate Sustainability Reporting Directive (CSRD²), is not expected until 2025. It will initially apply to companies with more than 500 employees, and the detailed content of the climate-related disclosures has yet to be written.³

In this paper, we empirically investigate the influence of climate risks on financial stability using a dataset of 130 European financial institutions. To address some of the shortcomings of existing approaches, we developed a theoretical framework of the transmission of climate risks to financial institutions. With this framework, we estimate how

national climate conditions and extreme events affect financial stability measured at the individual financial institution and system levels. We considered four different measures of financial stability, two that apply to individual financial institutions, and two to the financial system as a whole. These measures are based on Z-scores, the probability of default, market conditions, and the volatility of the financial system. Our empirical analysis extends from January 2001 to December 2021 for physical risks and from 2016 to 2021 for transition risks. Transition risk is measured by GHG emissions (Scope 1 and 2) and Scope 3. Physical risks, both chronic and acute, are measured using actual historical climate data. Our empirical work follows the work initiated by Dell et al. (2012, 2014) and Burke and Hsiang (2015).⁴ Chronic risks are measured using temperature and precipitation anomalies rather than average values, as unexpected deviations from climate normals are a more representative measure of risk associated with climate variability (Bertrand et al., 2015).

We find that transition risk measured as Scope 1 and 2 has limited influence on financial stability, which is consistent with Ehlers et al. (2022) who find that the price of transition risk is low. This result is likely explained by the fact that financial institutions are low GHG emitters. Most of their transition risk depends on the GHG emissions of the companies they finance, which fall within the Scope 3 of banks.

Focusing on European financial institutions that publish Scope 3 emissions, the results show that transition risk has a highly significant negative influence on the financial stability at both institution and financial system levels. This result is important. Given the low proportion of companies and banks that disclose Scope 3, it implies that the transition risk as currently estimated in the literature using mandatory climate-related disclosures (i.e., Scope 1 and 2) is most likely underestimated. It also highlights the importance for companies and banks to estimate and disclose Scope 3 emissions, and for regulators to publish legally binding methodological guidelines for estimating and reporting them.

With respect to physical risks, we show that temperature anomalies have a very significant influence on the financial stability of institutions and the system as a whole. This result demonstrates that the chronic risk, which has long been known to influence the economic and financial activity of many firms, is transmitted to the banks that finance them, and to the financial system as a whole. The influence that we measure, although very significant, is once again likely to be underestimated, given the annual time step used in this study, which prevents us from the ability to measure the additional effects of intra-annual climate variability (Starr-McCluer, 2000). The physical risk we identify at the individual level relates to heat waves, drought, and wildfires, consistent with the ECB EU economy-wide first stress-test. Although often considered to have primarily a local influence, we show that extreme events such as storms and tornadoes, together with heat waves, drought and forest fires, influence financial stability at the level of the eurozone system. The relative difference in significance between the institution level (low) and the system level (high) may be related to the amplification effects within the financial system, mainly due to a high degree of interconnectedness between financial institutions (Chabot et al., 2023). This again is an important result.

Our results contribute to the growing literature on climate risk and financial stability. Our approach accounts for the fact that climate risk is primarily local and specific, but its impact can be widespread and affect a wide range of other financial institutions. Our method overcomes the current lack of geo-located data, and demonstrates that climate risk materially affects individual financial institutions and the financial system as a whole. The speed at which the climate is changing, and the increasing intensity of extreme events, which in most European countries has already reached the intensity predicted for the end of the

² The 2022/2464 Directive of 14 December 2022 can be found here: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32022L2464>.

³ The European Commission is meant to adopt the first set of standards by mid-2023, based on the draft standards published by European Financial Reporting Advisory Group (EFRAG) in November 2022. The first set of draft of European Sustainability Reporting Standards (ESRS) is accessible at <https://EFRAG.org/lab6>.

⁴ See Kolstad and Moore (2020) for a comprehensive review of empirical methods to measure the effects of climate on economic indicators.

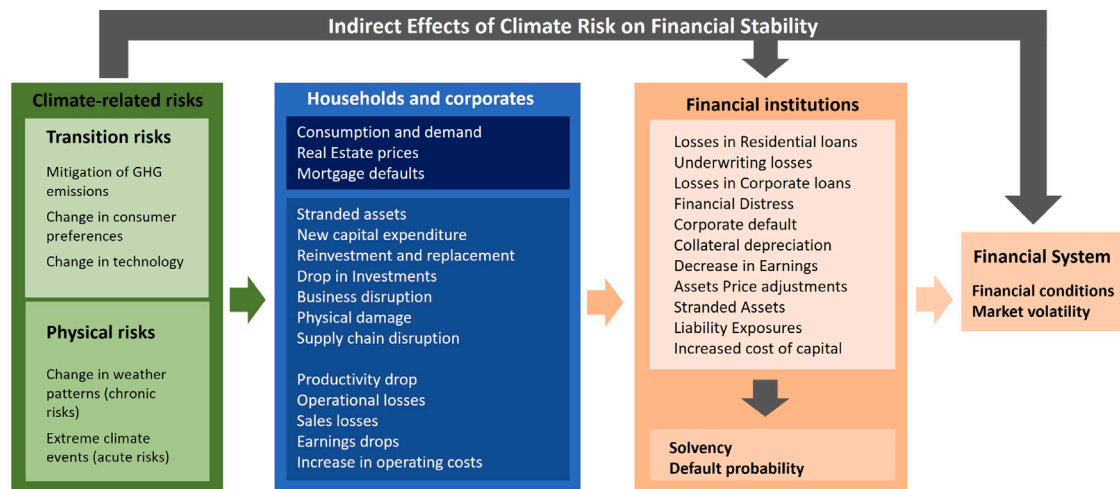


Fig. 1. Theoretical framework.

Chronic climate risks include temperature and precipitation anomalies; Acute climate risks include flooding, wild fires, cold and heat waves, droughts, storms, tornadoes, and hurricanes. The categories and list of extreme events are displayed in Table 1.

century by IPCC scenarios, call for new methods of risk measurement. Our method provides an alternative measure of climate-related risks that can be used to plan adaptation strategies and implement short-term risk reduction mechanisms. Our empirical results on physical risks urge regulators to issue mandatory climate-related corporate disclosures and adapt prudential capital requirements to climate-related risks.

The remainder of the paper is organized as follows. In the next section, we provide an overview of the relevant literature. Section 3 presents data and describes the empirical methodology. Section 4 presents the results and discusses them in relation to the existing literature. Section 5 concludes.

2. Theoretical framework

As part of the supervisory work on the transparency of banks' risk profiles, the European Central Bank assessed the level of climate-related risks disclosures of European financial institutions (ECB, 2022). The ECB concluded that *virtually none of the financial institutions in the scope of the assessment met the minimum level of disclosures expected by the ECB*. As a result, there is a lack of information on the nature, the location, and the value of bank assets exposed to climate risks. This does not currently allow a direct assessment of the influence of climate conditions and events on bank risks and financial stability. To overcome this issue, we designed a theoretical transmission model of climate-related risks (Fig. 1) that builds on two streams of the literature: physical climate risks and their impact on the economy, and transition risk and its influence on corporates and financial institutions.

We start by considering how physical climate risks affect households and corporates. Climate variability affects demand and consumers' purchasing decisions of a myriad of products. Climate variability globally affects 70% of corporates (Larsen, 2006). Retailers have long been aware that deviations from normal climate conditions affect sales. Early work on the influence of climate variability and its impact on corporate revenues dates back to Steele (1951), Linden (1962), and Maunder (1973). Starr-McCluer (2000) and Lazo et al. (2011) extend the analysis to US retail sales at the level of the U.S., while Parnaudeau and Bertrand (2018) show that the cumulative annual contribution of temperature and precipitation can have a material effect on corporate sales and cash-flows in large variety of activity sectors. Similarly, climate variability

can affect the supply and operating costs, as in the case of the agri-food industry (Kumar et al., 2022) or the construction industry (Schuldt et al., 2021). Further, the increase in climate variability that turns into weather shocks may lead to increased operating costs and lower productivity, and drive some businesses and industries to financial distress (Agnew and Palutikof, 2006; Dell et al., 2012; Cachon et al., 2012; Bertrand and Parnaudeau, 2019). The approach of estimating the influence of weather shocks on economic sectors and corporates is summarized in a survey paper by Dell et al. (2014). The effects of climate variability (chronic risks) on corporates as listed in the "Households and corporates" box of Fig. 1 include consumption and demand, productivity drop, operational losses, sales losses, earnings drops and increased operating costs.

Extreme weather events (acute risks) can cause temporary or permanent business interruptions, affecting companies' production assets or affecting their partners in the supply and distribution chains (Pankratz and Schiller, 2022). An extensive body of literature and news articles have documented the impact of natural disasters on global supply chains (see for instance Bland and Kwong, 2011 or Abe and Ye, 2013). Evidence also shows that acute physical risks reduce corporate profitability and potentially increase credit risk. Studies based on historical data find that natural disasters can result in short-term moderate declines in corporate sales. For example, US corporates have been shown to experience an average drop of 2 to 3 percentage points in sales growth, following a major natural disaster that affects their suppliers, ultimately causing a 1% drop in corporates' equity value (Barrot and Sauvagnat, 2016). Weishi Gu and Hale (2023) and other related studies (Schuldt et al., 2020; Nagar and Schoenfeld, 2022; Jia et al., 2022) show that extreme events influence corporate investments, negatively immediately after, and positively in the long-run. Noth and Schuwer (2018) find that extreme climate events increase the predicted probability of default as well as non-performing asset ratios, and reduce bank equity ratios. Extreme events also affect household wealth, and credit capacity. There is empirical evidence of property value declines resulting from damage caused by extreme climate events such as flooding (Bin and Polaski, 2004; Ortega and Taspinar, 2018), although the magnitude of the effect, and how long it persists, vary. In Fig. 1, these effects are listed as business disruption, supply chain disruption, physical damage, reinvestment and replacement, drop in investments, real estate prices, and mortgage defaults.

Transition risks stand on the concept of disorderly low-carbon transition. They refer to the economic and financial losses arising from a sharp revaluation of carbon-intensive and low-carbon assets, induced by a sudden change in policy and/or regulation that cannot be fully anticipated by corporate risk managers and financial actors (NGFS, 2019; Monasterolo, 2020). The climate policies needed to achieve a net-zero carbon economy by 2050 require a rapid and drastic transformation of industrialized and developing economies (e.g., in their energy, production, and consumption systems). These policies may have significant economic consequences, negative or positive, on many economic sectors, leading to adjustments in the value of financial assets held or issued by companies and sovereign entities. Firms may face higher operating expenses because of a higher tax on GHG emissions (Bernardini et al., 2019). The impact of this tax could reduce profits and the ability to meet debt repayments, and affect the company's creditworthiness. In turn, this could limit the access to funding, and increase the cost of such funding. Increases in credit costs for corporates in certain sectors may curtail their ability to invest in new technologies and equipment required to transition their business. Empirical evidence suggests that the 2015 Paris Agreement resulted in a higher cost of credit for corporates in polluting industries, for example fossil fuel companies (Seltzer et al., 2022; Delis et al., 2019). In addition, corporates whose business and revenues depend on the production or use of fossil fuels may suffer asset losses, resulting in so-called "stranded assets". These losses could in turn negatively impact the value of these corporates, and reduce their ability to get access to credit (Battiston et al., 2021). In Fig. 1, these additional effects are listed in "the Households and corporates" box as stranded assets and new capital expenditure.

We now examine how financial losses to households and businesses caused by climate-related risks can affect banks (box "Financial institutions" in Fig. 1). The increase in climate variability and in the number and intensity of extreme events is causing more and more damage to real estate and other productive assets, not all of which are insured. Over the last two decades, the number of extreme climate events in Europe has gone up by 35%, but the associated economic and financial losses have jumped by almost 60%, 40% of which are not insured (Monasterolo, 2020; European Environment Agency, 2022). These losses can in turn negatively impact the value of financial contracts and financial portfolios exposed to these assets, such as bank loans and pension fund stocks and bonds. Cortes and Strahan (2017) and Ivanov et al. (2022) show how extreme events affect bank lending and credit conditions. Mallucci (2020) and Klomp (2017) highlight the effects of climate risks on the pricing of sovereign debt and capital markets. Pagliari (2023) analyzes the impact of floods on small European banks, and shows that an adverse event leading to a decrease in lending to households and businesses results in a decline in the return on assets of these banks. In Fig. 1, we list these effects in the "Financial institutions" box as losses in residential loans, underwriting losses, asset price adjustments, decrease in earnings, and collateral depreciation. Like non-financial companies, banks and other financial institutions are exposed to transition risk. Although their direct emissions (Scope 1) are structurally low, indirect emissions from lending and investment (Scope 3) have the same potential impact on banks as those experienced by businesses, i.e., asset price adjustments, decrease in earnings, stranded assets, increased cost of capital, and financial distress (Roncoroni et al., 2021; Kacperczyk and Peydró, 2021; Reghezza et al., 2021; Ehlers et al., 2022).

The theoretical framework we built (Fig. 1) highlights the channels through which climate-related risks can influence financial stability across households and corporates. The lack of data on the location of assets exposed to climate risks makes it virtually impossible to measure directly the impact on financial institutions and the financial system (horizontal arrows). However, the theoretical framework and the literature on which it is based allow us to consider indirect measures of the impact of climate risks on financial institutions and the financial system. This is represented in Fig. 1 by the upper arrows,

which link climate risks to the solvency and default probability of financial institutions, and to market volatility and financial conditions in the financial system. The next section describes the data, variables, and methodology.

3. Data and methodology

Our study covers the period from January 2001 to December 2021 and is supported by several databases. Financial and accounting data as well as GHG and Scope 3 data are sourced from a Bloomberg terminal. The climate data used for chronic physical risk are daily temperature and precipitation observations from national meteorological services (see in Appendix Table 8). Temperature and precipitation climate data range from January 1991 to December 2021 to allow for the calculation of seasonal averages as defined by the World Meteorological Organization (WMO, 2017). Extreme events for acute physical risk were retrieved from the BD CatNat from Ubyrisk.

3.1. Sample

Our analysis is exploratory by nature, and takes the approach of extending the perspective to a sample of financial institutions with different risk profiles and climate exposures, from systemically important financial institutions (SIFIs) to regional banks, provided that financial information is available over a relatively long period of time. We built a representative database of the European financial system by selecting cooperative, mutual, and listed financial institutions of different sizes (see Chabot (2021) for a discussion of the features of the European banking markets). The geographical breakdown of the 130 financial institutions in the panel, for which we had a complete set of variables, is provided in Appendix (Table 9). Table 1 at the end of this section summarizes the variables used in this paper.

3.2. Dependent variables: Financial stability measures

Financial stability is measured using successively four different variables: Z-score (Z), Default Probability (DP), Bloomberg Financial conditions (BFC), and Market volatility (V). Z and DP are bank-level measures of financial stability. BFC and V are financial system level measures. Z-scores are widespread measures of financial stability. We follow Laeven and Levine (2009), Lepetit and Strobel (2015), Tonzer (2015), and Noth and Schuwer (2023) and define Z for each bank i over the time period t as:

$$Z_{it} = \frac{ROA_{it} + EA_{it}}{\sigma_{ROA}} \quad (1)$$

ROA is the Return on Assets, EA is Equity over total Assets, and σ_{ROA} the standard deviation of the Return on Assets.

DP measures the 5-year probability of default. DP incorporates fundamental factors such as sector risk, market sentiment, and the economic cycle to determine the probability of default. DP is estimated by Bloomberg following Merton (1974), Altman and Sabato (2005), Altman (2010). It is based on a combination of measures such as profitability (ROA, ROE), capital structure, liquidity (liquid assets and size), market information (distance-to-default measures), and an estimate of insolvency based on the study of the institution's equity.

BFC index assesses the overall level of financial stress in the euro area (based on money, bond, and equity markets) to determine the availability and cost of credit. A positive value indicates accommodative financial conditions, and a negative value indicates tight financial conditions. Finally, V is the Vstox index of the Eurozone. Its US equivalent is known as the VIX index. V is estimated using a methodology developed jointly by Goldman Sachs and Deutsche Börse. The higher the index, the greater the volatility of the market (Osina, 2019).

Table 1
Summary list and description of variables.

Abbrev.	Variable	Description
Z	Z-score	Measure of financial stability of each financial institution
DP	Default Probability	Measure of default probability of each financial institution
BFC	Financial Conditions	Measure of overall level of financial stress in the euro area based on credit availability estimated by Bloomberg
V	Volatility	Measure of overall level of financial stress measured by Vstoxxx
RGDP	Real GDP	Real Gross Domestic Product per country
3M	Money market rate	3-month money market rate
PX	Asset Price	Daily closing price of each financial institution
ITBA	Interbank Assets	Interbank assets of each financial institution
NPA	Non-Performing Assets	Non-performing assets of each financial institution
T1	Tier-1	Tier 1 Capital of each financial institution
GHG	Emissions 1 & 2	Scope 1 and 2 GHG emissions of each financial institution
Scope 3	Emissions 3	Scope 3 GHG emissions of each financial institution
ANOT	Temperature Anomaly	Average difference between observed temperatures and their 30-year average
ANOP	Temperature Anomaly	Average difference between observed precipitations and their 30-year average
HYD	Hydrological	Number of Flooding and mudflow events
CLI	Climatological	Number of Forest fires, coldwaves, heatwaves, and droughts
MET	Meteorological	Number of cyclones, storms, hail, tornadoes, waterspouts, blizzards, avalanches, and freezing rain

Z, DP, BFC, and V are the dependent variables; GHG and Scope 3 are transition risk variables; ANOT and ANOP are chronic climate risk variables; HYD, CLI, and MET are acute climate risk variables. They represent the number of material events classified level 3 or above in each risk category; RGDP, 3M, PX, ITBA, NPA, T1 are economic and financial variables.

3.3. Independent variables

3.3.1. Economic variables

The economic variables we use are the determinants of financial stability identified in the literature. Following Caccioli et al. (2013), Brunetti et al. (2015), Kanno (2015), Liu et al. (2015), Paltalidis et al. (2015) and Chabot (2021), we use asset price (PX), interbank assets (ITBA), non performing assets (NPA), and Tier 1 (T1). We also use real GDP growth rate (RGDP) and the 3 month money market rate (3M) (Battiston et al., 2012; Tonzer, 2015; Embree and Roberts, 2009).

3.3.2. Transition risk variables

To test the influence of transition risk on financial stability, we use both “Total GHG emissions” and “Scope 3” published by Bloomberg. Total GHG emissions is the sum of Scope 1 GHG emissions + Scope 2 emissions. Scope 1 covers direct emissions from owned or controlled sources of the financial institution. Scope 2 covers indirect emissions from the generation of purchased electricity, steam, heating and cooling consumed by the financial institution. The E.U. requires large companies to report their environmental and social impact, as part as their non-financial reporting. This is covered under the Non-Financial Reporting Directive (NFRD), or Directive 2014/95/EU. It is important to note that reporting scope 1 and 2 is not a requirement of the NFRD, which simply requires companies to publish the non-financial report. Companies can still exclude scope 1 and 2 from their report.

Financial institutions are typically low-emitting companies. Direct emissions are likely to be small relative to indirect emissions. While companies that fall within NFRD may report Scope 1 and 2, the reporting on scope 3 is scarcer than scope 1 and 2 (EFRAG, 2021). In the absence of a legally binding regulation, the best practices in the field of corporate emissions accounting and reporting have been developed through the cooperation of non-governmental organizations and non-profit institutions. Examples include the GHG Protocol (WRI and WBCCSD, 2021), the Global Reporting Initiative (GRI) and the Sustainability Accounting Standards Board (SASB), among others. The most widely used framework to account and report corporate GHG emissions in the EU is the GHG Protocol developed by the cooperation between the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD). This international standard covers the accounting and reporting of seven greenhouse gases included in the Kyoto Protocol.

The absence of a legally binding GHG measurement methodology has some implications on the quality of the data, and its consistency across data providers. An emerging literature on GHG data quality identified some inconsistencies, gaps, and omissions in the way emissions are disclosed in sustainability reports, and across different channels (Dragomir, 2012; Talbot and Boiral, 2018; Papadopoulos, 2022). Inconsistencies are found to be low in direct emissions, and progressively increase in indirect emissions (Busch et al., 2022).

This is likely due to the fact that Scope 1 and 2 are mandatory in most countries but the disclosure of Scope 3 is voluntary. In addition, the scope of disclosure for Scope 3 can vary over time for a single company and also between companies, as disclosures practices for Scope 3 can vary (Mandyck, 2022). Scope 3 data from Bloomberg include all indirect emissions other than Scope 2 that occur in a company’s value chain, such as purchased goods and services, business travel, employee commuting, waste disposal, use of sold products, transportation and distribution (up- and downstream), investments, and leased assets. In the case of financial institutions, Scope 3 also includes GHG emissions related to loans and investments. Scope 3 is likely to be the most significant transition risk variable, and should allow to directly link financing and investments to emissions. Due to the fact that Scope 3 emissions have mainly started to be reported after the Paris agreements in 2015, the analysis period considered for the transition risk is 2016–2021. This period also applies to Scope 1 and 2 data for reasons of comparability of results.

3.3.3. Chronic risk variables

Climate variability can influence the activity of the financial institution directly and indirectly through the influence on the companies to which it lends or in which it has invested. The construction of a relevant climate variable can be done in a bottom-up approach under the conditions that (1) each financial institution publishes the geographic distribution of loans and investments related to its customers, and (2) their customers in turn publish the geographic distribution of their activities. As this is not the case, we built on Fig. 1 to develop metrics aimed at capturing the combined direct and indirect influence on each financial institution. These dependent and explanatory variables are positioned on the theoretical framework at the end of this section (Fig. 2).

In the specific case of Europe, banks’ corporate and retail clients are mainly domestic (Chabot, 2021). Alogoskoufis et al. (2021) find that across countries, banks have a strong home bias, giving loans predominantly

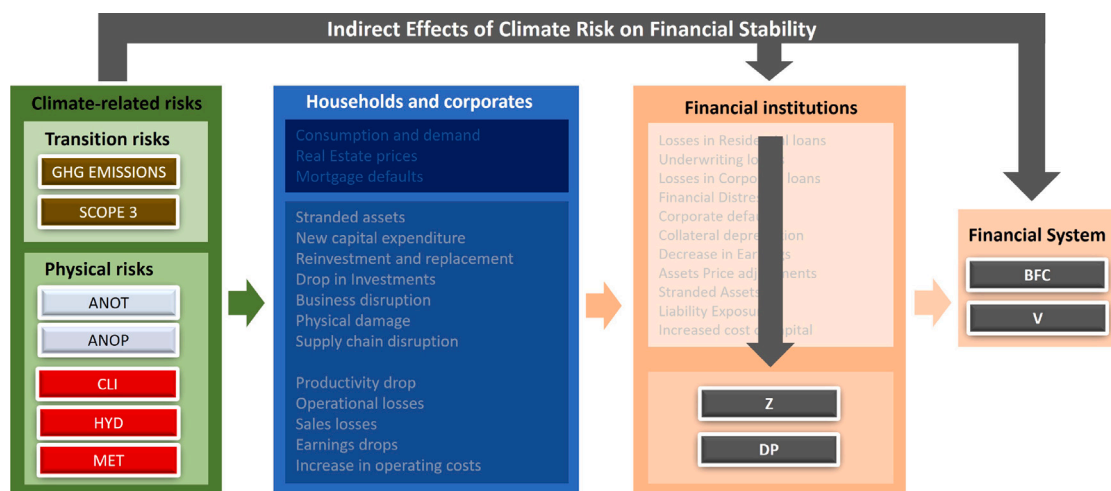


Fig. 2. Explanatory and dependent variables in the theoretical framework.

Z, DP, BFC, and V are the dependent variables; GHG and SCOPE 3 are transition risk variables; ANOT and ANOP are chronic climate risk variables; HYD, CLI, MET are acute climate risk variables; Data are annualized when used in the models.

to domestic rather than foreign firms (...). In all countries, with the exception of Ireland and Luxemburg, domestic firms make up at least 50% of bank portfolios and at euro area level 80% of banks' exposures are to domestic firms. The composition of bank portfolios in terms of domestic versus foreign firms determines the extent to which the country-level climate risk of the firms (...) translates into country-level climate risk for banks. Another study from Duijm and Schoenmaker (2017) analyzes the proportion of domestic and European assets relative to total assets on a panel of the 61 largest European banks. The information about the distribution of assets between domestic and non-domestic markets is not readily available, and data was hand-collected. The study confirms that a large proportion of the assets are either domestic or European. In relative terms, a small proportion of the assets is outside of the combined "domestic and rest of Europe" (see Appendix Table 15).

In addition, annual temperature and precipitation anomalies are highly correlated between neighbor countries. For instance, if there is a warm temperature anomaly in France in a given year, the same anomaly is usually experienced in neighbor countries, such as Germany, Italy, or Belgium (see Appendix Fig. 4). Temperature anomalies in France can be considered a proxy of German, Italian, or Belgian temperature anomalies. The strong emphasis of banks' assets on "domestic and rest of Europe" reinforces the relevance of building national indices to explore the influence of chronic climate risks.

Following Quayle and Diaz (1980), Parsons (2001), and Dell et al. (2014), and following World Meteorological Organization's guidelines for creating a set of national climate indices (WMO, 2017), the chronic risk variables for each country are the aggregate of the climate data for all stations in the country, weighted by the corresponding population data assigned to each station. The concept in creating a country climate index to be used in economic or financial models is to reproduce the average climate conditions experienced by economic actors in the considered area, not the average climate conditions experienced in the area. The chronic risk variables we built in this paper are derived from daily observations of temperature and precipitation measured across a wide range of ground weather stations in each European country. The number of stations in each country is the one used by the national meteorological office to calculate temperature or precipitation to produce national climate indices. This number depends on the number of climatically homogeneous geographical areas needed for the national index to be representative. The number of stations is different for temperature and precipitation. It also differs from country

to country, depending on the size and geography of the country. Due to the granularity of the financial data, the chronic climate data used in the models are annual. The daily data were converted to annual data using a calibration method.⁵

3.3.4. Acute risk variables

Access to data on extreme weather events is more challenging as most databases are not public and by construction contain some bias. Biases are reflected in damage thresholds, the nature of the events, the completeness of the description of the events, their localization, their consequences, and the countries covered. We analyzed four of the most complete databases: BD Catnat, Munich Re, Swiss Re, and CRED.⁶ A comparison of the databases over the period 2001–2021 indicates that the total estimated damages are similar between the 4 databases: 3797 billion US dollars for BD Catnat, compared to 3752 for Munich Re, 3604 for Swiss Re, and 3066 for CRED. In terms of number of events and completeness, BD Catnat is the most exhaustive, with 18,080 events compared to 16,294, 3218 and 7278 respectively. Extreme events in the BD Catnat database are grouped into three categories: hydrological (HYD), climatic (CLI) and meteorological (MET). They cover a wide range of climatic hazards, from floods and freezing rain to fires and storms. In this analysis, we consider all the events of natural origin that caused a material damage. The word material is to be understood in its accounting definition, i.e., significant enough to warrant reporting to investors, insurers, or other stakeholders. The damages apply to both material goods and people. Each event is classified on a scale of 1 to 5 according to its degree of materiality. Level 1 and 2 events are local (town, county) and have limited damage (no human consequence, and partial damage to buildings). They are excluded from our database. Level 3 and 4 events have a spatial extension to one or more regions,

⁵ The complete process to transform daily temperature and precipitation data into monthly, quarterly, or annual temperature and precipitation anomaly indices is developed in Bertrand et al. (2015), Bertrand and Parnaudeau (2017).

⁶ Munich Re and Swiss Re are reinsurance companies, CRED is maintained by the University of Leuven (Belgium), and BD Catnat is from Ubyrisk, a private risk management consulting firm. Other providers include the Asian Disaster Reduction Center, EMA (Australia), the Federal Emergency Management Agency (USA), and Reliefweb.

or to a country, and have a significant human or material cost, or both. Level 5 extends to several countries. For the purpose of this analysis, we included all events classified levels 3 to 5. In the database, each event is assigned to a country. A level 5 event is assigned to all countries that have suffered damage in connection with the event.

3.4. Methodology and models

The influence of climate risks on financial stability is carried out using panel data models. Kolstad and Moore's (2020) recent literature review on statistical approaches applied to climate and economics showed that the use of panel data is highly relevant when the research question aims to understand the response of a system as a whole to climate change (Deschênes and Greenstone, 2007; Dell et al., 2012; Burke and Hsiang, 2015; Colacito et al., 2019). In particular, panel data allows us to assess the conceptual aspects over time by analyzing a succession of years of observations of the same financial institutions and, for a given year, over the total observed population. We first estimate the impact of economic and financial variables on financial stability measured by four different dependent variables (Z and DP at bank-level, and BFC and V at system-level). We then test the influence of transition risk on financial stability by successively testing Total GHG and Scope 3 emissions. Finally, we test the influence of physical risks, both chronic and acute. In step 1, the model is as follows:

$$FS_{it} = \alpha_i + \beta(\text{EcoFin})_{it} + \epsilon_{it} \quad (2)$$

where FS_{it} is financial stability successively measured at the individual level of each financial institution by Z and DP, and at the financial system level by BFC and V. EcoFin_{it} gathers asset prices (PX), 3 month money market rate (3M), real GDP (RGDP), interbank assets (ITBA), non performing assets (NPA), and Tier one (T1). In this model and the next three models, α_i is a constant and ϵ_{it} is the disturbance term. In step 2, we add transition risk variables to Eq. (2) as follows:

$$FS_{it} = \alpha_i + \beta(\text{EcoFin})_{it} + \gamma(\text{Transition})_{it} + \epsilon_{it} \quad (3)$$

where Transition_{it} is successively "GHG" and "Scope 3" emissions. In step 3, we add physical risk variables to Eq. (2) as follows:

$$FS_{it} = \alpha_i + \beta(\text{EcoFin})_{it} + \delta(\text{Physical})_{it} + \epsilon_{it} \quad (4)$$

where Physical_{it} gathers chronic risk variables, i.e., anomalies of temperature (ANOT) and anomalies of precipitation (ANOP), and acute risk variables, namely the number of hydrological extreme events (HYD), climatic extreme events (CLI), meteorological extreme events (MET).

4. Results and discussion

This section presents and discusses the results of the influence of transition and physical climate risks on financial stability at bank and system levels. The presentation of the results follows the steps of the methodology. The results are reported in the same format, displaying the influence of each explanatory variable and its significance on financial stability, at the individual financial institution level (columns Z and DP in each table in this section), and at the system level (columns BFC and V). In each table, significance at the .01, .05, and .10 level is represented by ***, **, and * respectively.

4.1. Descriptive statistics and correlation analysis

Descriptive statistics are summarized in Table 10 in Appendix. A focus on chronic risk variables shows that the average temperature anomaly of the last decade (2011–2020) across our panel of European countries is 0.39 °C higher than the first decade (2001–2010). This is consistent with WMO's statement confirming that temperatures in Europe have increased at more than twice the global average over the past 30 years. In addition, from one decade to the next, the standard deviation of temperature anomalies increased by almost 50%, from

0.32 °C to 0.48 °C, further confirming the rise in climate variability. Average precipitation over the same periods however did not exhibit any trend or significant change in the standard deviation. These statistics are in line with the IPCC reports which indicate that the annual cumulative precipitation has been globally constant in Europe. Its distribution over the year however shows that the summer months are increasingly dryer to the benefit of the winter months which are wetter (IPCC, 2021).

A focus on acute risk variables, i.e., extreme events, shows that extreme events increased both in terms of the number of events (+33%) and their financial consequences (+62%), in line with the findings of the latest (IPCC, 2021) report. In the database of European extreme climate events, events categorized as meteorological were the most frequent (54%), followed by climatic events (29%) and hydrological events (17%).

A correlation analysis between the financial stability variables and the set of explanatory variables was carried out (see Table 11 in Appendix). We verified the absence of significant correlations between climate risk variables. We verified that all series of variables are stationary. We also confirmed the absence of endogeneity between the dependent variables and the climate variables, and the absence of clustering (country or period), autocorrelations or outliers in the residuals. We can thus proceed to the analysis of the estimation of the models.

4.2. Financial stability and control variables

As a first step, we confirm the relationships between economic and financial variables and financial stability (Table 2). Results are in line with the relevant literature (Chabot, 2021). At the individual level, Z is positively influenced by an increase in stock market returns (PX), short-term interest rates (3M), and Tier 1 (T1). The probability of default (DP) decreases when PX and T1 increase. DP increases when 3M and non-performing assets (NPA) increase. At system level, financial conditions (BFC) improve with an increase in stock returns and Tier 1, and a decrease in short-term rates. Volatility (V) decreases with an increase in PX, 3M, and real GDP (RGDP), and increases when NPA rises.

4.3. Financial stability and transition risk

We add total GHG emissions to the model and test their influence on financial stability over the past five years. The relationships observed previously are confirmed, except for non-performing assets for which we observe a decrease in both the value of the coefficients and the level of significance. Real GDP however is now significant in 3 models out of 4 (Table 3).

At bank level, we find that an increase in GHG emissions has a negative effect on Z with a level of significance of only .1. At the system level, higher emissions are associated to lower financial conditions (BFC) and higher volatility (V). Again, the level of significance is only .1. The fact that DP is not significant can be explained by the information and statistical indicators which do not include environmental issues. These results are nevertheless consistent with the fact that Scope 1 and 2 of financial institutions is low. Therefore, the level of transition risk exposure is low when transition risks are measured by the only two Scopes that banks are required to disclose. We next investigate the influence of Scope 3. As scope 3 disclosure is done on a disparate and voluntary basis in Europe, the proportion of financial institutions in our database that disclose Scope 3 is about 20%. This is consistent with the fact that only 15% of the 109 European banks they supervise publish data as part of Scope 3 on the emissions of the companies they finance (Arnold, 2022).

Financial institutions' exposure to transition risk is mainly indirect and Scope 3 is likely to be much larger than Scope 1 and 2. Financial institutions cover virtually all activity sectors as they finance public

Table 2
Financial stability and economic and financial variables.

	Z	DP	BFC	V
PX	.19*** (2.05)	-.05*** (-2.53)	2.25*** (3.78)	-7.006*** (-3.22)
3M	.10*** (1.87)	-.02*** (-2.65)	-8.54*** (-11.56)	1.79*** (6.64)
RGDP	.01 (.37)	.006 (.26)	.78 (1.66)	-9.67*** (-5.63)
ITBA	.87 (.95)	-.33 (-1.30)	-4.401* (-1.56)	1.16 (1.13)
NPA	-3.79*** (-6.09)	1.01*** (3.15)	-19.47* (-1.74)	6.96** (1.71)
T1	.90*** (1.93)	-.41*** (-2.10)	3.07*** (3.96)	-4.39* (-1.55)
c	.03** (1.67)	.03*** (4.94)	.90*** (3.17)	19.74*** (18.98)
F-statistic	3.13***	2.91***	2.36***	1.34***
Cross-section F: fixed effects	yes	yes	no	no
Cross-section Chi-Square : fixed effects	yes	yes	no	no
Hausman test: random effects	no	no	no	no
Estimation under the presence of SE Clust.	f.e	f.e	f.e	f.e
R Sq.	.56	.55	.51	.53
Adj. R Sq.	.48	.47	.45	.45

Z and DP are individual level measures of financial stability; BFC and V are Eurozone system level measures of financial stability; RGDP, 3M, PX, ITBA, NPA, and T1 are economic and financial variables. Data are annualized when used in the models. All variables are stationary. F-test is a test a joint relevance of the variables in the models. R-sq. is the goodness of fit. The Hausman test verifies the presence of random effects. SE Clust. verifies the absence of standard error clustering (period and cross-sections). Results apply to 2001–2021.

Table 3
Financial stability and GHG emissions.

	Z	DP	BFC	V
PX	.91* (1.56)	-.33* (-1.49)	3.49 (1.21)	-6.01* (-1.50)
3M	3.47*** (2.64)	.24 (.86)	-5.12*** (-2.12)	5.74*** (1.95)
RGDP	1.04*** (2.28)	-.14 (-1.37)	.31*** (4.45)	1.82*** (2.31)
ITBA	-1.52*** (-1.82)	.07** (1.81)	1.79* (1.48)	-3.63** (-1.70)
NPA	-1.42 (-.91)	1.3*** (2.36)	-7.96* (-1.37)	2.61* (1.61)
T1	1.51*** (3.52)	-.30*** (-2.90)	2.63* (1.20)	-5.96* (-1.62)
GHG	-9.28* (-1.36)	3.80 (1.22)	-2.22* (-1.61)	3.71* (1.55)
c	.93*** (2.86)	-.02 (-.34)	-16.79*** (-2.53)	197.69*** (2.55)
F-statistic	3.93***	2.67***	1.09***	6.36***
Cross-section F: fixed effects	no	no	no	no
Cross-section Chi-Square: fixed effects	no	no	no	no
Hausman test: random effects	yes	yes	yes	yes
Estimation under the presence of SE Clust.	r.e	r.e	r.e	r.e
R Sq.	.58	.51	.38	.41
Adj. R Sq.	.51	.43	.21	.32

Z and DP are individual level measures of financial stability; BFC and V are Eurozone system level measures of financial stability; GHG are Scope 1 and Scope 2 emissions of individual financial institutions that measure transition risk; RGDP, 3M, PX, ITBA, NPA, and T1 are economic and financial variables. Data are annualized when used in the models. All variables are stationary. F-test is a test a joint relevance of the variables in the models. R-sq. is the goodness of fit. The Hausman test verifies the presence of random effects. SE Clust. verifies the absence of standard error clustering (period and cross-sections). Results apply to 2016–2021.

and private companies. If reporting carbon emissions of loans and investments, Scope 3 emissions should be significant and allow to identify their influence on financial stability. This is what our results confirm (Table 4). At bank level, Scope 3 emissions negatively affect Z.

Table 4
Financial stability and Scope 3 emissions.

	Z	DP	BFC	V
PX	1.24** (2.21)	-.004 (-.05)	17.81** (2.13)	-192.2** (-2.14)
3M	.21*** (5.86)	.01 (.45)	-.56 (-1.42)	27.69*** (6.51)
RGDP	.16*** (2.73)	-0.02 (-.91)	12.04*** (6.87)	107.74*** (5.70)
ITBA	-1.05 (-.82)	.08 (.28)	10.04*** (2.57)	108.36*** (2.57)
NPA	-7.09** (-2.89)	.97*** (2.16)	-81.80*** (-6.78)	882.74*** (6.78)
T1	1.31** (1.72)	-.13* (-1.58)	17.10*** (2.9)	-184.59*** (-2.90)
Scope 3	-1.75*** (-2.92)	3.93 (.94)	-3.09*** (-3.27)	3.34*** (3.27)
c	-.006 (-.16)	.03*** (4.82)	-3.95*** (-13.88)	59.06*** (19.22)
F-statistic	2.96***	1.98**	20.35***	21.51***
Cross-section F: fixed effects	no	no	yes	yes
Cross-section Chi-Square: fixed effects	yes	yes	yes	yes
Hausman test: random effects	yes	yes	no	no
Estimation under the presence of SE Clust.	r.e	r.e	f.e	f.e
R Sq.	.39	.34	.9	.9
Adj. R Sq.	.29	.24	.83	.84

Z and DP are individual level measures of financial stability; BFC and V are Eurozone system level measures of financial stability; Scope 3 are Scope 3 (indirect) emissions of individual financial institutions that measure transition risk; RGDP, 3M, PX, ITBA, NPA, and T1 are economic and financial variables. Data are annualized when used in the models. All variables are stationary. F-test is a test a joint relevance of the variables in the models. R-sq. is the goodness of fit. The Hausman test verifies the presence of random effects. SE Clust. verifies the absence of standard error clustering (period and cross-sections). Results apply to 2016–2021.

At system level, an increase in Scope 3 has a negative effect on financial conditions and increases market volatility. The results are significant at the .01 level.

These results on Scope 3 and financial stability are insightful in a context where Blackrock, a founding member of Task Force on Climate-Related Financial Disclosures (TCFD) and one of the largest asset managers in the world, advocates for a *flexible approach to rule-making based on “comply or explain”, rather than mandating complete Scope 3 disclosures in annual and quarterly reports*. In the US, under the March 2022 climate-related rule proposal of the SEC, registrants would be obligated to disclose their greenhouse gas emissions for their most recently completed fiscal year. All filers except smaller reporting companies would also be required to disclose their Scope 3 emissions if the Scope 3 emissions are material, or if the registrant has a target or goal that includes Scope 3 emissions. Blackrock's comments are not intended to allow companies and banks to escape disclosure of Scope 3 emissions, especially since Blackrock, in a recent letter to CEOs, admits that *as investors, they use Scope 3 emissions as a proxy for the degree of exposure companies have to carbon-intensive business models and technologies*. The market criticisms of the proposed Scope 3 requirements focus on ambiguities in data collection and measurement, calculation methodologies, timing of deadlines, and materiality standards. Given our results on Scope 3, it is critical that market regulators and the bodies in charge of the main reporting frameworks (e.g., TCFD, IASB) align their objectives and resources to select a common methodology for calculating and disclosing Scope 3. Our results also show that transition risk as it applies to financial institutions, when GHG emissions are limited to Scope 1 and 2, is likely to be underestimated.

4.4. Financial stability and physical risks

We now consider the influence of both chronic and acute climate events on financial stability (Table 5).

At bank level, temperature anomalies (ANOT) have a significant influence on Z and DP. Both are significant at the .01 level. Academics have long demonstrated the influence of temperature on economic activity (Deschênes and Greenstone, 2007; Dell et al., 2014; Burke and Hsiang, 2015; Newell et al., 2021). Banks' exposure to temperature anomalies is mainly indirect. Our results confirm that chronic climate risks are indeed transmitted from the real economy to the financial system via banks and financial institutions. Climatic events (e.g., heatwaves, droughts, wildfires) is the only category of extreme events for which we find a significant influence, but only at the .1 level. Climatic extreme events influence both Z and DP, again, at the .1 level. This result is consistent with Alogoskoufis et al. (2021), who found wildfires to be a significant risk to financial stability, although in our study we did not measure the specific influence of wildfires, which are considered collectively with heat waves, cold waves, and drought as a single physical risk variable (CLI). This result is also consistent with Acevedo et al. (2020) and Miller et al. (2021) on weather shocks and heatwaves on output and GDP, and earlier related findings from Nordhaus (2006), Burke et al. (2009), and Cachon et al. (2012).

At system level, temperature anomalies have a very significant influence on both BFC and V. In addition, two categories of extreme events have a very significant impact on financial stability, namely climatic events and meteorological events (e.g., storms). Both are significant at the .01 level. These results are all the more remarkable as the level of aggregation of the data likely underestimates the effects of climate risks. Indeed, a cold anomaly can have negative consequences on a given activity sector in Q2, while a warm anomaly of the same size in Q3 also has negative consequences. This is the case for the apparel industry for instance (Bertrand et al., 2015). In this example, when aggregating the data annually, cold and warm anomalies offset each other. There is no temperature anomaly, and therefore no ability to measure the two quarterly losses yet due to temperature. This phenomenon has been identified by Starr-McCluer (2000), who gave it the name of wash-out effect. The difference of significance level between bank-level (low) and system-level (high) may be explained by the compounding and amplification effects identified in the literature, which is mainly due to the interconnections between financial institutions (Chabot et al., 2023). The high level of significance of the market indicators (BFV and V) may also be explained by the fact that extreme weather and climate events affect large areas and are associated with significant damage, both financial and human. This is especially true in the case of storms and tornadoes.

Overall, our results are in line with the findings of existing scenario and stress-test analyses (Battiston et al., 2017; Vermeulen et al., 2019; Reinders et al., 2020; NGFS, 2019; Allen et al., 2020; Roncoroni et al., 2021): physical and transition risks significantly affect financial stability at bank and system levels (Coelho and Restoy, 2022). They are also in line with Noth and Schuwer (2023), who find that in the U.S., *weather-related natural disasters significantly weaken the stability of banks with business activities in affected regions*.

4.5. Robustness

We used several tests to confirm the robustness and relevance of the models. The F-test is a joint test that supplements the Student's tests and allows to validate the explanatory variables in the tested models. If significant, the variables are collectively relevant in explaining the dependent variable. The Cross-section F and Cross-section Chi-square tests evaluate the presence of fixed effects. The Hausman (1978) test verifies whether the random effects (r.e) estimation is more relevant than the fixed effects (f.e) estimation method. In addition to these tests, we controlled for ESG scores. The ESG scores used here were provided by S&P Global Ratings. ESG scores from S&P Global ratings range from 2016 to 2021.

Table 5

Financial stability and physical climate risks.

	Z	DP	BFC	V
PX	.93 (1.43)	−.009 (−.35)	1.32*** (1.88)	−1.08*** (−2.11)
3M	3.85*** (2.85)	.03 (.04)	−5.12*** (−9.30)	5.74*** (3.39)
RGDP	.98*** (2.10)	−.04 (−.23)	.31*** (2.81)	1.88*** (−4.97)
ITBA	−1.95* (−1.59)	.1 (.43)	1.39 (1.22)	8.51 (.87)
NPA	−3.30* (−1.61)	.41 (.58)	9.31 (1.82)	1.51*** (3.75)
T1	1.56*** (3.13)	−.36*** (−2.11)	9.25*** (2.92)	−6.99*** (−3.27)
ANOT	−.005*** (−3.14)	.003*** (1.95)	−3.12*** (−4.27)	1.13*** (3.66)
ANOP	.015 (.34)	.05* (1.46)	6.21 (.44)	9.89 (.21)
CLI	−.0011* (−1.38)	.0006* (1.34)	−7.16*** (−2.62)	1.83*** (2.31)
HYD	.002 (.58)	.0024 (.91)	−9.80 (−1.26)	−1.18 (−.41)
MET	.0001 (.84)	−1.87 (−12)	−3.19*** (−2.84)	1.44*** (2.03)
c	1.03*** (3.08)	.11* (.50)	−16.79*** (−1.11)	197.69*** (4.29)
F-statistic	2.94***	1.83**	1.49***	2.10***
Cross-section F: fixed effects	yes	yes	no	no
Cross-section Chi-Square: fixed effects	yes	yes	no	no
Hausman test: random effects	yes	yes	yes	yes
Estimation under the presence of:	r.e	r.e	r.e	r.e
SE Clust.	No	No	No	No
R Sq.	.51	.6	.4	.43
Adj. R Sq.	.43	.54	.24	.13

Z and DP are individual level measures of financial stability; BFC and V are Eurozone system level measures of financial stability; ANOT and ANOP are climate chronic risk variables; CLI, HYD, and MET are climate acute risk variables; RGDP, 3M, PX, ITBA, NPA, and T1 are economic and financial variables. Data are annualized when used in the models. All variables are stationary. F-test is a test a joint relevance of the variables in the models. R-squ. is the goodness of fit. The Hausman test verifies the presence of random effects. SE Clust. verifies the absence of standard error clustering (period and cross-sections). Results apply to 2001–2021.

ESG rating agencies offer investors a way to screen companies for ESG performance in a similar way to how credit ratings allow investors to screen companies for creditworthiness (Berg et al., 2020). ESG ratings are broken down into many indicators and hierarchies, the first level of which is Environment (E), Social (S), and Governance (G). Pillar E is at times used in the literature as a proxy for measuring transition risk when no other measures are available, due to the fact that GHG emissions and mitigation strategies are important components of the E-score. S&P Global ESG Scores are proprietary data that result from a combination of verified company disclosures, media and stakeholder analysis, and in-depth engagement activities with companies. Entity-specific scores are assessed on a relative basis, against sector peers. The Scores range from 0 to 100. Scores of 0 to 25 indicate poor ESG performance and insufficient transparency in the public reporting of material ESG data. Scores above 75 indicate excellent relative ESG performance and a high degree of transparency. We limit the study period of the influence of ESG to the most recent years (2016–2021) for comparability reasons. Table 12 in the Appendix summarizes the main elements that make up the different E, S, and G pillars.

The first additional control variable we consider is the environmental score (E). The E-score is primarily influenced by the level of emissions and mitigation strategies that have been implemented, or that are being considered, to reduce risk. The analysis of the individual pillars confirms that E has an influence on financial stability both at bank and system levels (Table 6). As E increases, Z decreases, and V increases. Results are significant at .05 and .01 respectively. This is in line with existing literature: environmentally-active institutions (high

Table 6
Financial stability and E Scores.

	Z	DP	BFC	V
PX	.06 (.03)	−1.45*** (−2.11)	4.3 (1.37)	−34.44*** (−3.40)
3M	2.732*** (2.43)	.1 (.24)	−5.12*** (−2.33)	1.45 (.50)
RGDP	.81*** (3.24)	−.21*** (−3.09)	.31*** (6.15)	5.33*** (7.88)
ITBA	−3.18*** (−4.01)	−.05 (−.30)	−1.35 (−.56)	4.56 (.43)
NPA	−1.25 (−.60)	.29 (1.31)	3.9 (1.98)	−28.02*** (−2.72)
T1	5.48*** (3.56)	−.87*** (−3.17)	−3.04 (−1.13)	11.35** (1.72)
E	−2.26** (−2.08)	.22*** (2.62)	−5.01 (−.42)	1.3** (1.81)
c	.69** (2.80)	.07* (0.62)	−16.79*** (−2.86)	20.90*** (18.73)
F-statistic	6.82***	1.84***	1.66*	7.03***
Cross-section F: fixed effects	yes	yes	no	no
Cross-section Chi-Square: fixed effects	yes	yes	no	no
Hausman test: random effects	no	no	no	yes
Estimation under the presence of:	f.e	f.e	f.e	r.e
R Sq.	.83	.58	.46	.28
Adj. R Sq.	.71	.26	.18	.24

Z and DP are individual level measures of financial stability; BFC and V are Eurozone system level measures of financial stability; RGDP, 3M, PX, ITBA, NPA, and T1 are economic and financial variables; E is the environmental score from S&P Global Ratings. Data are annualized when used in the models. All variables are stationary. F-test is a test a joint relevance of the variables in the models. R-squ. is the goodness of fit. The Hausman test verifies the presence of random effects. SE Clust. verifies the absence of standard error clustering (period and cross-sections). Results apply to 2016–2021.

E) are associated to a lower risk (Bouslah et al., 2018). With respect to the S score and the G score, we find that G scores are negatively associated to the probability of default (DP) at the .05 level (see Tables 13 and 14 in Appendix). This is consistent with Pastor et al. (2021) and Bernile et al. (2018). We also find that S scores negatively impact DP with a .01 level of significance. At system level, we find that G has an influence on V, but with a low level of significance. Better customer engagement, board oversight, controls, transparency, and values together (high S and G) result in better management, higher profitability, and lower risks as perceived by shareholders and markets (Friede et al., 2015; Chambers et al., 2018).

ESG scores are often used as “financial soundness” proxy variables, and as such, they should lower the risk. At financial institution-level, Table 7 shows that ESG scores have a significant influence on Z at the .01 level. The higher the ESG score, the stronger the financial stability. Again, the influence on DP is however not significant. At system-level, BFC is the only financial stability variable that is influenced by ESG overall scores, only at the .1 level. The higher ESG scores, the better financial conditions. The results are consistent with Chiaramonte et al. (2015), who find that the ESG overall score, as well as its sub-pillars, reduce bank fragility during periods of financial distress. Companies with high environmental, social and governance scores tend to have higher excess returns, lower cost of capital, lower volatility, and therefore lower exposure to tail risks (Friede et al., 2015; La Torre et al., 2020; Giese et al., 2019).

4.6. Recommendations

Central banks as well as academia have highlighted that the risks of inaction with respect to climate-related risks are far greater than the risks of acting on the basis of partial data (NGFS, 2019; Coelho and Restoy, 2021). Policy makers and supervisors are gradually agreeing on the need to revise the prudential framework to take full account of

Table 7
Financial stability and ESG overall scores.

	Z	DP	BFC	V
PX	2.34 (1.01)	−.02 (−1.06)	5.36* (1.56)	−32.17** (−1.81)
3M	2.386** (1.90)	.79*** (8.97)	−5.12 (−2.40)	3.6 (.22)
RGDP	.50* (1.50)	−.42*** (−10.71)	.31*** (5.17)	5.38*** (2.41)
ITBA	−2.77 (−1.23)	−.02 (−.62)	−4.02* (−1.61)	−14.7* (−1.47)
NPA	−.85 (−.27)	.76** (1.71)	1.29* (1.62)	−37.4* (−1.42)
T1	8.15*** (8.46)	−.20** (−2.08)	4.92* (1.63)	14.30*** (2.47)
ESG	.305*** (3.06)	2.98 (1.22)	5.71* (1.60)	4.9 (.30)
c	.39* (1.19)	−.11*** (−2.53)	−16.79*** (−3.04)	20.63*** (2.57)
F-statistic	11.41***	2.58***	1.50***	6.13***
Cross-section F: fixed effects	yes	no	no	no
Cross-section Chi-Square: fixed effects	yes	no	no	no
Hausman test: random effects	no	yes	yes	yes
Estimation under the presence of:	f.e	r.e	r.e	r.e
R Sq.	.93	.42	.48	.27
Adj. R Sq.	.85	.33	.31	.23

Z and DP are individual level measures of financial stability; BFC and V are Eurozone system level measures of financial stability; RGDP, 3M, PX, ITBA, NPA, and T1 are economic and financial variables; ESG is the ESG rating from S&P Global Ratings. Data are annualized when used in the models. All variables are stationary. F-test is a test a joint relevance of the variables in the models. R-squ. is the goodness of fit. The Hausman test verifies the presence of random effects. SE Clust. verifies the absence of standard error clustering (period and cross-sections). Results apply to 2016–2021.

the implications of climate-related risks for financial stability (Carney et al., 2019; Baranovic et al., 2021). Potential gaps may exist in the Pillar 1 framework for operational risks, since it does not cover losses related to strategic and reputational risks, the latter of which may be closely related to transition, liability, or environmental risks. Supervisory measures and enhanced climate-related disclosures represent important tools for the financial sector, to better guard against climate risks in the short and medium term. Pillar 1 captures losses related from inadequate or failed internal purposes, people, and systems or from external events. This includes, at least conceptually, some aspects of climate risks materializing in actual physical damages of the bank assets, or liability risk reflected in legal or compliance risk. In contrast, Pillar 2 covers risks which are underestimated or not covered by Pillar 1. Given the challenges of capturing the impact of climate-related financial risks, some of the principles and methodologies underpinning the Basel Pillar 1 framework might not hold. In particular, how and when these risks will manifest over different time horizons creates uncertainty in addition to existing uncertainties related to climate and associated economic long-term scenarios. Some parts of the current prudential framework are backward-looking, as they rely on consistent, historical data to gauge the relationships between risk factors and exposures to which our findings can contribute. Pillar 2 is a natural candidate for ensuring that banks effectively report and manage physical climate risks, and have sufficient loss-absorbing capacity against them.

The process of modifying the macroprudential framework to take account of short- and long-term climate risks, however, requires reinforced measures to standardize, enforce, and monitor corporate climate-related risk information. In turn, the ability of financial institutions to assess their own climate risk is dependent on the quality of climate-related disclosures provided by the companies they invest in or lend to (Feridun and Gungor (2020). The moves from the UK government and the SEC to make TCFD-aligned climate risk disclosure mandatory is a step in the right direction (Simpson, 2022).

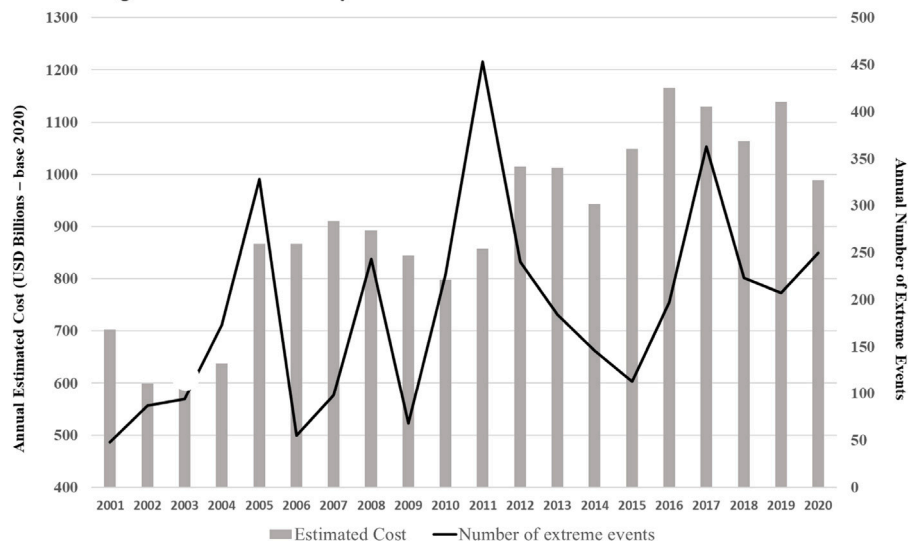


Fig. 3. Acute physical climate risk annual statistics*. *: France, Germany, Italy, Spain, and the United-Kingdom.

	Aus	Bel	Fin	Fra	Ger	Gre	Ita	Net	Spa	Swe	UK
Austria	1,00	0,45	0,16	0,55	0,63	0,58	0,65	0,41	0,47	0,19	0,03
Belgium		1,00	0,70	0,99	0,97	0,48	0,32	0,99	0,46	0,86	0,42
Finland			1,00	0,67	0,61	0,44	0,35	0,74	0,38	0,93	0,03
France				1,00	0,98	0,54	0,99	0,99	0,35	0,80	0,40
Germany					1,00	0,64	0,46	0,95	0,23	0,77	0,27
Greece						1,00	0,86	0,53	0,45	0,36	0,53
Italy							1,00	0,39	0,57	0,16	0,43
Netherlands								1,00	0,44	0,86	0,36
Spain									1,00	0,56	0,72
Sweden										1,00	0,26
UK											1,00

Fig. 4. Correlation between annual temperature anomalies across major European countries.

Table 8

Anomalies of temperature and precipitations: Data Sources.

Country	Source
Austria	Zentralanstalt für Meteorologie und Geodynamik
Belgium	Royal Meteorological Institute
Finland	Finnish Meteorological Institute
France	Meteo-France
Germany	Deutscher Wetterdienst
Greece	Hellenic National Meteorological Service
Ireland	Met Éireann
Italy	Servizio Meteorologico
Netherlands	Koninklijk Nederlands Meteorologisch Instituut
Spain	Agencia Estatal de Meteorología
Sweden	Swedish Meteorological and Hydrological Institute
Switzerland	MeteoSwiss
UK	Met Office

5. Concluding comments

In this paper, we analyze the influence of transition and physical climate risks on financial stability on a panel of European financial institutions using a top-down approach. We find that both transition and physical climate risks significantly influence financial stability. An increase in Scope 3 emissions and climate variability, both chronic and acute, has a negative effect on financial stability at the level of each institution and at the level of the financial system.

Our results complement the growing literature on climate risk and financial stability. One specificity of climate risk is that it is mostly local, but its impact can be widespread, depending on the nature of the risk and its intensity. The theoretical framework we propose builds on the transmission channels from the real economy, which has long been known to be exposed to climate risks, to the financial system through financial institutions and their high level of interconnectedness. In a context of accelerating climate change and climate variability, the method we expose should be considered in addition to existing methodologies to offer regulators and risk managers the opportunity to improve short-term risk assessment and adjust capital requirements to both short-term and long-term horizons. Our results stress the importance of using climate variables and actual extreme events to assess the short-term exposure of financial institutions based on actual climate variability and historical extreme events, to complement long-term existing scenario-based models.

Our findings support the need for mandatory corporate climate risk disclosures so that financial institutions are able to value their

climate-related risk exposures in their lending and investment portfolios. Finally, in a context of rising climate variability, our results suggest that climate risk should be factored into prudential regulations as early as possible.

Data availability

Data used in this study are not publicly available as they are derived from proprietary databases. This is the case for climate and extreme event data, Bloomberg financial data, and ESG scores from S & P, which the authors have access to through subscriptions and agreements between national meteorological agencies and the research organization with which they are affiliated. Data are available from the corresponding author upon reasonable request, subject to the agreement of the owner of the requested data.

Appendix

A.1. Tables and figures

See Figs. 3 and 4 and Tables 8–15.

Table 9

Geographical distribution of financial institutions.

Country	Number of Financial Institutions	Percentage in the sample
Austria	10	8%
Belgium	12	9%
Finland	4	3%
France	12	9%
Germany	12	9%
Greece	9	7%
Ireland	3	2%
Italy	12	9%
Netherlands	10	8%
Spain	12	9%
Sweden	11	8%
Switzerland	11	8%
United Kingdom	12	9%
Total	130	100%

Table 10

Descriptive statistics of variables.

Financial stability variables	Mean	Std	Median	Min	Max
Z	.233	1.02	.09	−21.76	8.27
DP	.0231	.037	.016	.0002	.763
BFC	−.62	1.92	.03	−7.39	1.14
V	23.17	9.16	21.76	13.51	51.21
Economic Variables					
PX	118.75	313.02	28.46	.0004	4062
3M	1.37	1.73	.85	−.57	4.86
RGDP	1.08	2.51	1.90	−10.80	11.40
ITBA	38.030	75.504	4878	18.35	787,295
NPA	9221	18.35	4127	.15	297,725
T1	24,408	33,770	9700	−2070	383,783
Transition risk variables					
GHG	2058	36,755	39.55	.06	693,606
Scope 3	151.5	970.9	7.80	.02	9,912.1
Physical climate risk variables					
ANOT	.85	1.10	.70	−.54	9.26
ANOP	.98	.09	.98	.74	1.26
HYD	2.21	2.47	1.00	.00	8.00
CLI	4.59	9.20	1.00	.00	40.00
MET	10.90	16.43	6.00	.00	66.00
ESG variables					
ESG Overall	60.86	26.80	65.00	2.00	99.00
E	64.40	23.98	67.00	10.00	99.00
S	60.58	26.29	62.00	.00	98.00
G	57.63	28.94	63.00	3.00	99.00

Table 11

Correlation matrix between financial stability and physical risk variables.

	Z	DP	BFC	V	ANOT	ANOP	HYD	CLI	MET
Z	1								
DP	−.4354	1							
BFC	.1810	−.3278	1						
V	−.1747	.0409	−.4767	1					
ANOT	.0766	−.0053	−.2369	−.2862	1				
ANOP	.0482	−.0055	.1815	.1372	−.2043	1			
HYD	.1331	.0007	−.0368	−.0216	−.1189	.1618	1		
CLI	.1020	−.0144	.0853	.0641	−.0316	−.1157	.2139	1	
MET	.1381	−.0064	−.0098	−.0278	.0614	−.0421	.2217	.2533	1

Table 12

S&P Global ESG Scores, (2016–2021)

Score (Variable)	Description
ESG (ESG)	Overall ESG score
Environmental score (E)	Greenhouse Gas Emissions Waste and Pollution Water Use Land Use
Social (S)	Workforce and Diversity Safety Management Customer engagement Communities
Governance (G)	Structure and Oversight Code and Values Transparency and Reporting Financial and Operational risks

Table 13

Financial stability and Social (S) Scores.

	Z	DP	BFC	V
PX	.11 (.05)	−1.48*** (−2.09)	2.90** (2.009)	−37.26*** (−2.17)
3M	3.151*** (3.94)	.11 (.27)	−4.17*** (−3.01)	1.45 (.09)
RGDP	.90*** (4.74)	−.21*** (−3.41)	.30* (1.47)	5.30*** (2.36)
ITBA	−3.11*** (−6.20)	−.03 (−.26)	−.43 (−.45)	7.49 (.63)
NPA	−1.15 (−.55)	.31 (1.38)	2.22 (.99)	−27.41 (−1.05)
T1	5.74*** (3.30)	−.92*** (−3.78)	−.86** (−1.97)	12.21*** (2.34)
S	1.14* (1.52)	−.22*** (−3.90)	9.9 (1.07)	1.4* (1.48)
c	.71*** (3.20)	.07* (.62)	−1.86*** (−2.61)	21.00*** (2.71)
F-statistic	6.52***	1.84***	17.88***	7.11***
Cross-section F: fixed effects	yes	yes	no	no
Cross-section Chi-Square: fixed effects	yes	yes	no	no
Hausman test: random effects	no	no	yes	yes
Estimation under the presence of:	f.e	f.e	r.e	r.e
R Sq.	.83	.58	.50	.28
Adj. R Sq.	.70	.26	.47	.24

Table 14

Financial stability and Governance (G) Scores.

	Z	DP	BFC	V
PX	.47 (.22)	−1.36** (−1.92)	2.90** (2.04)	−37.30*** (−2.24)
3M	3.682*** (3.70)	.11 (−.24)	−4.15*** (−3.03)	1.14 (.07)
RGDP	1.005*** (4.36)	−.22*** (−3.19)	.39* (1.47)	5.30*** (2.36)
ITBA	−3.18*** (−4.42)	−.10 (−.55)	−.60 (−.54)	10.02 (.75)
NPA	−1.21 (−.53)	.23 (1.29)	2.09 (.96)	−25.48 (−1.01)
T1	6.51*** (4.62)	−.77*** (−2.65)	−.90** (−1.91)	12.81*** (2.26)
G	.03 (.09)	−.10** (−1.82)	1.06 (1.03)	−1.61* (−1.42)
c	.75*** (2.54)	.06* (.52)	−1.53*** (−2.64)	20.88*** (2.73)
F-statistic	6.36***	1.84***	17.84***	7.14***
Cross-section F: fixed effects	yes	yes	no	no
Cross-section Chi-Square: fixed effects	yes	yes	no	no
Hausman test: random effects	no	no	yes	yes
Estimation under the presence of:	f.e	f.e	r.e	r.e
R Sq.	.82	.58	.52	.27
Adj. R Sq.	.69	.26	.46	.21

Table 15

Geographical distribution of assets per country as a percentage of total assets.

Source: Adapted from : Duijm and Schoenmaker, 2017.

	Domestic	Rest of Europe	Total
France	66.4	20.4	86.8
UK	55.0	8.8	63.8
Germany	50.2	24.7	74.9
Spain	47.4	26.9	74.3
Netherlands	61.2	23.5	84.7
Italy	67.7	29.3	97.0
Sweden	48.8	46.3	95.1
Belgium	59.2	37.1	96.3

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