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Climate Interconnectedness and Financial Stability

Miia Chabot^{a,*}, Jean-Louis Bertrand^b, and Valentin Courquin^c

ABSTRACT

Climate risks directly affect a wide range of non-financial firms, and indirectly affect the financial institutions that lend to or invest in them. In this paper, we explore the influence of climate risks on financial stability of European financial institutions using network analysis and panel regressions. The determination of interconnectedness variables and the graphical representations of climate networks allow the identification of climate systemic important financial institutions and risk concentrations. Our work contributes to the development of new macroprudential metrics to capture climate risks and address climate-related risk from a systemic perspective.

RÉSUMÉ

Les risques climatiques affectent directement de nombreuses entreprises non financières et indirectement les institutions financières qui les financent. Dans cet article, nous explorons l'influence des risques climatiques sur la stabilité financière des institutions financières européennes en utilisant l'analyse des réseaux et les régressions en panels. La mesure des variables d'interconnexion et les représentations graphiques des réseaux climatiques permettent d'identifier les institutions financières d'importance systémique et les concentrations de risques. Notre travail contribue au développement de nouvelles mesures macroprudentielles en permettant d'identifier les risques climatiques et de les gérer d'un point de vue systémique.

KEYWORDS Financial Stability, Physical Climate Risk, Transition Risk, Networks, Interconnectedness, Prudential Policy

JEL CLASSIFICATION Q51, Q54, G21, G22, G28, L14, D85

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1. Introduction

Climate change is becoming a major financial stability issue and one of the most important challenges facing global economies (Alt et al., 2015; Carney, 2015; WEF, 2022; Ranger et al., 2022). The consequences of climate change are systemic in nature (Aglietta and Espagne, 2016). They affect the whole planet, through rising variability, accumulated GHG emissions, and localized extreme events that can propagate to larger territories using different channels, physical, social, and financial. Climate change incorporates in fact the three components that define systemic risk, namely contagion risk, macro shock risk, and the risk of unravelling imbalances accumulated over time (ECB, 2009).

Banks play a central role in the economy through the choices they make about the activities they finance and the assets they invest in, as the 2007 financial crisis has highlighted (Cornett et al., 2016; Berger et al., 2017). The financial system's exposure to climate change is mostly indirect, but significant enough that 102 central banks and supervisors joined forces in 2017, explicitly considering climate risks as part of a supervisory mandate, and challenging policymakers, other central banks, and supervisors to act to limit the catastrophic impacts of runaway climate change (NGFS, 2019). The Financial Stability Board (FSB) has identified three main channels through which climate change can affect financial stability, and has defined the risks associated with each channel using the terminology of transition, physical, and liability risk (Carney, 2015). *Transition* risk refers to the financial risks that the implementation of climate policies and regulation poses directly to high-emitting companies and indirectly to their lenders and investors. *Physical* climate risks refer to the financial impact on economic activity and financial assets of climate variability, encompassing both extreme weather events and gradual changes in climate. Physical risks are termed “acute” when they arise from extreme events including tornadoes, storms, flooding, droughts, or forest fires, and “chronic” when they result from progressive shifts, including climate variability driven by the effects of elevated temperatures (ECB, 2020). Finally, *liability* risks relate to financial compensation for victims of climate change insofar as a court can make a company legally liable for the climate-related damage suffered.

This paper is motivated in particular by the ECB's recent commitment to take greater consideration of the potential impact of physical climate

risks on the financial system. Indeed, in assessing the effects of climate change on financial stability, the initial focus has been mainly on transition risk (Bressan and Romagnoli, 2021; ECB, 2021). However, given the increase in climate variability, the ECB is concerned that physical climate risks could comparatively be more consequential and that amplification mechanisms arising from the concentration of exposures, correlation of cross-risks, and overlapping portfolios of financial institutions may reinforce this concern. In addition, given the lifetime of GHG emissions already accumulated and the inertia of the atmospheric system, no significant improvement in climate variability is possible before 20 to 30 years, whatever the emission reduction scenario. It is therefore necessary to measure the financial consequences of physical risks in order to put in place the necessary tools and adaptation measures (Battiston et al., 2021; Ranger et al., 2022). This paper is also motivated by the European Securities and Markets Authority's decision in early 2022 to create a new risk category that distinguishes climate risk from other categories, including liquidity, market, credit, contagion, and operational risks, in its risk management, assessment, and monitoring framework, and to encourage the emergence of climate-specific risk monitoring indicators to measure the systemic nature of climate risk and possible "amplification mechanisms". In particular, regulators fear market sell-offs due to the lack of information on banks' exposure to physical weather risks. In this regard, the ECB acknowledged that none of the 115 lenders it supervises are currently meeting their climate risk disclosure obligations (Arnold, 2022; Elderson, 2022). In addition, half of these banks admitted to being "materially" exposed to climate risks (Elderson, 2022). One important objective of this paper is to explore the effects of physical climate risks by examining how they affect individual financial institutions (Z-score and Default Probability) and how they affect the European financial system as a whole (Financial Conditions and Volatility).

In this paper, we empirically investigate the influence of physical climate risks and transition risks on financial stability using a dataset of 130 European financial institutions. Our empirical analysis extends from January 2000 to December 2021. The analysis is conducted in three steps. The first step consists in examining the correlation of chronic, acute climate risks (number and costs), and transition risks with various measures of financial stability. The second step focuses on the nature of the interconnections of financial institutions related to climate risks and the

visualization of these networks. The third step of this work is to test the influence of climate risk factors and their climate interconnectedness measures on European financial stability, using panel regressions. To assess the influence of climate variability, we use temperature and precipitation anomalies (Bertrand et al., 2015). The potential effects of physical climate risk on financial stability are measured using a proprietary database that exhaustively records all extreme climate events since 2000, their geographical location and propagation, their duration, and their human and financial cost. The cost is cross-estimated from multiple sources (reinsurers, governments, NGOs). Transition risk is measured using CO₂ emissions. We consider four different measures of financial stability. Two of them apply to individual financial institutions, and the other two apply to the financial system as a whole. These measures are based on financial performance, probability of default, market conditions and the volatility of the financial markets.

First, we show that chronic and acute physical climate risks significantly influence financial stability. Second, as we compare the influence on financial stability of climate variables and interconnectedness variables in climate networks, we find that there is a phenomenon of amplification of climate risks within the financial system. Third, in comparing the influence of climate network interconnectedness variables on financial stability to conventional financial interconnectedness variables, we find that the influence of climate risk is of comparable magnitude to the influence of conventional financial parameters used by regulators to monitor systemic risk. Fourth, network analysis based on climate risk categories and climate interconnectedness measures provide the opportunity to identify financial institutions at risk and potential risk concentrations. To our knowledge, this is the first time that climate networks constructed from climate and extreme event data have been used to identify the influence of climate risks on the financial stability of institutions and the system in which they operate. In particular, network analysis allows us to build an analytical database of interconnectedness characteristics by financial institution, to observe their evolution over time, and to identify among financial institutions those that should be monitored closely, either because of their importance in the network or because of their individual exposure to the consequences of climate risks. This study contributes to the development of new tools and metrics to measure climate risks and

capture their systemic consequences. It also contributes to filling the gaps in the current prudential framework related to material climate risks.

The remainder of the paper is organized as follows. The next section describes the Data. Section 3 presents the conceptual framework and methodology. Section 5 discusses the descriptive statistics of variables, and the main results. Finally, section 6 concludes and offers some policy implications.

2. Related literature

In the literature, measures of systemic risk can be organized into two broad approaches (Bisias et al., 2012; Billio et al., 2016). A first approach links financial institutions to the market and relies on conditional Value-at-Risk (Adrian and Brunnermeier, 2011) or Marginal Expected Shortfalls (Acharya et al., 2010), and pays particular attention to the study of financial return tails. The second approach focuses on the networks of connections between financial institutions (Battiston et al., 2012; Loepfe et al., 2013; Barro and Basso, 2010; Mistrulli, 2011; Billio et al., 2016; Elliott et al., 2014; Elliott and Hazell, 2016). Based on the concepts of feedback centrality (Battiston et al., 2012), topology (Loepfe et al., 2013), and entropy (Barro and Basso, 2010; Mistrulli, 2011; Billio et al., 2016), this second approach allows to analyze the entire system, and to highlight the potential propagation channels. The risk of default of a large portion of the system is assessed on the basis of interconnectedness of financial exposures between institutions (Battiston et al., 2012; Elliott et al., 2014; Elliott and Hazell, 2016; Torri et al., 2018). Our study is embedded in this second approach and the emerging literature on the application of network analysis to climate risks (Battiston et al., 2017; Roncoroni et al., 2021; Zhang et al., 2022).

The literature on the relationship between climate risk and financial stability is still in its early stages (FSB, 2020). Most of the current work focuses on estimating the potential consequences of climate policies on *transition* risks, and projecting these consequences over the long-term using IPCC transition scenarios and data from integrated assessment models (McGlade and Elkins, 2015; NGFS, 2020). Dafermos et al. (2018) investigate climate change-induced financial instability and its feedback mechanisms using a stock-flow-fund ecological model. Stolbova

et al. (2018) highlight the limitations of existing economic models of climate policies effectiveness evaluation that ignore the role of the financial sector. They tend to overestimate their effectiveness by neglecting financial interconnectedness, contagion effects, and potential network feedback loops that can amplify negative shocks coming from climate policies. Safarzynska and van den Bergh (2017) show that systemic risk increases significantly if climate policy is implemented too late and too suddenly. When market participants do not anticipate this sudden policy change, adjustment costs are likely to be higher than expected and to foster financial instability (Battiston and Martinez-Jaramillo, 2018). Roncoroni et al. (2021) study the impact on financial stability of interactions between climate policy shocks and market conditions, designing a framework that they empirically apply to Mexican banks through contagion scenarios, adding to the mainstream literature on stress testing, a tool commonly used by financial authorities to assess the resilience of the financial system (Borio and Drehmann, 2014; Battiston et al., 2016; ECB, 2021). Lamperti et al. (2021) rely on emissions data to test the efficiency of green policies in their ability to reduce the climate risks. In a recent paper, Dunz et al. (2021) examine the ability of climate finance policies that support investment in green assets and penalize brown assets (high-emitting firms) to enhance financial stability. Dafermos and Nikolaidi (2021) takes a similar approach to test whether these policies can reduce *physical* risks, by redirecting credit availability and investment toward low-carbon assets. This leads to the other, less prolific strand of the climate risk literature, that explores the resilience of the financial system to *physical* risks. The development of this strand is hampered by the accessibility of data on extreme events, which are not as widely available as data on GHG emissions or climate policies. To overcome this obstacle, researchers resort to proxies, a recent example being the study of financial stability by Flori et al. (2021), which relies on the evolution of agricultural commodity prices, themselves influenced by climatic conditions. Bressan and Romagnoli (2021) consider weather derivatives and analyzes how their use can reduce exposure to physical weather risk and improve financial stability. Caby et al. (2022) use CDP scores, governance, management, and climate change strategy indicators, and country-specific climate risk scores as proxies for physical risks. Ranger et al. (2022) identifies shortcomings of widely used scenarios and available stress tests for physical climate financial risk scenarios, and proposes an additional approach called "realistic

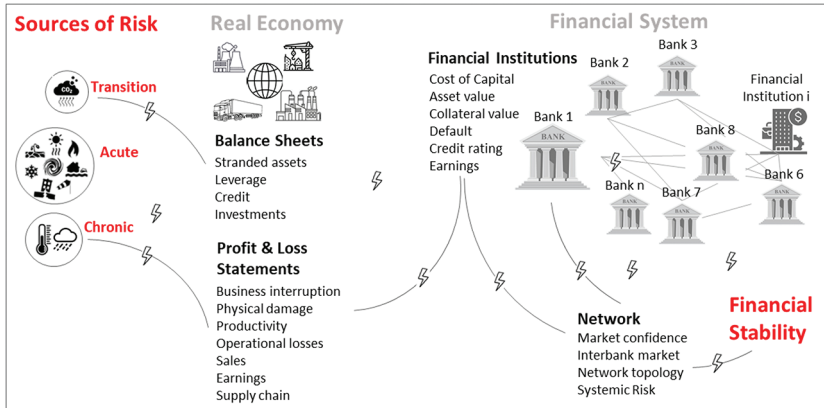
catastrophe scenario" derived from the insurance industry. They highlight inconsistencies in the extreme events considered, as well as uncertainties in climate models, compound scenarios, indirect economic impacts, and feedback loops between the financial sector and the real economy. Consistent with Stolbova et al. (2018), these uncertainties expose policy makers to underestimation of risk. They are barriers to mobilizing short-term financial resources to manage what is perceived as a long-term risk. However, to our knowledge, no study analyzes the impact of physical risk on financial stability by directly testing the influence of climate variability and extreme events. Similarly, no study considers the interconnection networks resulting from physical climate risks and their influence on financial stability. These are two gaps we propose to address. In this paper, we successively investigate the influence of climate risks on financial institutions and financial stability. The two hypotheses we test in this paper are: H1: Climate risks influence the default risk of financial institutions; H2: Climate risks have a systemic influence on financial stability.

3. Methodology and framework

The theoretical mechanism underlying the propagation of climate risk to the financial system is increasingly well understood (Carney, 2015; Aglietta and Espagne, 2016; Batten et al., 2016; Nieto, 2019; Bank of England, 2019; NGFS, 2020; TCFD, 2020; Bardoscia et al., 2021; ECB, 2021; Elderson, 2022). We have synthesized the different approaches to graphically illustrate how climate risk is transmitted from the real economy to the financial system (Figure 1).

Transition risk arises from a shock related to an abrupt change in climate policy or a sharp increase in the cost of carbon. This shock initially directly affects cash-flows and values of assets, increases the probability of default of the most exposed firms, spreads to the market for the loans and bonds that make up the assets of financial institutions, which themselves potentially face a drop in collateral value, and an increase of the cost of capital. The consequence is a deterioration of earnings and prudential ratios, a downgrading of their credit rating, financial distress for some, that can spread to other financial institutions within the network of the financial system. Chronic physical risks, i.e., too hot, too cold, too wet, too dry, affect demand, sales, productivity, earnings, and potentially credit rating of many firms, which again leads to a deterioration of cash-flows

Figure 1: Conceptual Framework of the Transmission Channels of Climate Risks. Adapted from Batten et al. (2016), TCFD (2020), NGFS (2020), and ECB (2021)



and earnings, and potential defaults on loans financial covenants or repayments. Acute physical risks cause direct impacts on productive assets, infrastructure, supply chains, and result in business interruption, leading to reduce trade and investments, reduced value of assets, increased cost due to recovery and reconstruction, all of which are transmitted to the financial system through the banks that are most involved with firms directly or indirectly affected by climate disasters.

Our methodology proceeds in three phases. Phase 1 consists in the study of the correlation between financial stability measures and transition risk, chronic, and extreme climate risks (number of events and cost). Phase 2 focuses on the interconnections between financial institutions resulting from climate risks. It consists in computing the interconnectedness variables, and then graphically visualizing the networks using a Kamada-Kawai algorithm (Kamada and Kawai, 1989). This algorithm allows to position the nodes of a network in a two-dimensional space in a way that minimizes the number of possible crossing edges, thus offering a simple and readable visualization of potentially complex networks. An important feature of a Kamada-Kawai graph is that the total balance of the layout is linked to each individual characteristic. Phase 3 and final phase in this work is to test the influence of climate risks and climate interconnectedness on financial stability, using panel regressions. Kolstad and Moore (2020)'s recent literature review on statistical approaches applied to climate and economics showed that the use of panel analysis 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 analysis 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.

4. Data and econometric model

Our study covers the period from January 2000 to December 2021 and is supported by several databases. Financial and accounting data are extracted from a Bloomberg terminal. GHG emissions are published by Eurostat. The climate data used for chronic physical risk are daily temperature and precipitation observations from national meteorological services. The climate data range from January 1991 to December 2021 to allow for the calculation of seasonal normals as defined by the World Meteorological Organization (WMO). Extreme events were retrieved from the BD CatNat from Ubyrisk. In this section, we describe the sample of financial institutions and the financial stability dependent variables. We then focus on the climate independent variables and define the climate network interconnectedness variables. The variables used in this study are summarized and described in Table 2.

4.1. *Sample of Financial Institutions*

The construction of Europe has gone hand in hand with the development of the European banking market, which has evolved considerably over the past decades. The initial deregulation has allowed players of very different sizes, legal and shareholding structures to cross national borders to grow within the EU. In a second phase, banking harmonization has spread with the implementation of the Single Supervisory Mechanism in November 2014, along with the Single Resolution Mechanism (Chabot, 2021). Some institutions have been taken over, others have merged, and others have appeared. While still more fragmented than the US market, the European financial market is such that financial institutions within the EU are all subject to identical monetary and prudential supervision, operate on liberalized banking markets, and face the same regulation regarding payment systems, financial services and capital mobility (Scholtens and

Van't Klooster, 2019). We also included insurance companies in our database to reflect two growing concerns. On the one hand, their activity makes them collectively the largest investors in Europe with a growing share of investments on risky assets in search of financial performance for their clients. They also share credit, operational and currency risks with banks. Finally, the increase in damages related to climate change is leading some central banks to question whether the current capital framework for insurance companies is “fit for purpose” when it comes to integrating climate risks (IAIS, 2011, 2016; Ellul et al., 2018; Grimaldi et al., 2020). In addition, financial markets are prompted to revalue assets that are directly or indirectly exposed to climate risks, which adds risk to insurers’ investment portfolios and their own stock market valuations. With this background, and since our work is exploratory by nature, we built a database of the European financial institutions of different sizes, different shareholders structures (public versus mutual), from systemically important financial institutions (SIFIs) to national to regional banks. The geographical breakdown of the 130 financial institutions for which we had a complete set of variables, is provided in Table 1. All financial data, both specific and market data, were extracted from Bloomberg.

4.2. Dependent variables: Financial Stability Measures

The individual risk of financial institutions and financial stability are measured using two sets of dependent variables: Z-score (Z) and Default Probability (DP) apply to individual risk, Bloomberg Financial Conditions (BFC) and Market volatility (V) measure financial stability of the financial system. Z-scores are widespread measures of financial stability (Boutin-Dufresne and Savaria, 2004; Basel Committee on Banking Supervision, 2015; Cornett et al., 2016; Bouslah et al., 2018). We follow Laeven and Levine (2009), Lepetit and Strobel (2015), Tonzer (2015), and Berger et al. (2017), and compute Z for each bank i over the time period t as:

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

ROA is the Return on Assets, EA is Equity over total Assets, and σ_{ROA} the standard deviation of the Return on Assets. Second, bank risk is directly measured through the 5-year probability of default (DP) estimated by Bloomberg. This estimate incorporates fundamental factors such as sector risk, market sentiment, and the economic cycle to determine the

Table 1: Breakdown of Financial Institutions per Country of Incorporation

Country	Number of Financial Institutions	Number of Banks
Austria	10	5
Belgium	12	2
Finland	4	1
France	12	8
Germany	12	8
Greece	9	4
Ireland	3	2
Italy	12	17
Netherlands	10	2
Spain	12	4
Sweden	12	8
Switzerland	11	8
United Kingdom	12	7
Total	131	76

probability of default. Default risk is calculated following Merton (1974), Altman and Sabato (2005), and 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.

The financial stability of the system is measured using the Bloomberg financial conditions index (BFC), which assesses the overall level of financial stress in the euro area based on money, bond, equity markets and the availability and cost of credit. A positive value indicates accommodative financial conditions, and a negative value indicates tight financial conditions. We also study the financial stability of the system with the market volatility (V) measured by the Vstoxx index of the Eurozone. Its US equivalent is known as the VIX index. Vstoxx is estimated using a methodology developed jointly by Goldman Sachs and Deutsche Borse. The higher the index, the greater the volatility of the market, the higher financial instability (Osina, 2019).

4.3. Independent variables

4.3.1. Physical Climate Risk Variables

Chronic and acute physical climate risk variables combine measures of climate variability and extreme events respectively. Climate variability variables are based on daily observations of temperature and precipitation measured across a wide range of ground weather stations in each European country so as to create country temperature and precipitation national indices.

In the specific case of Europe, banks' corporate and retail clients are mainly domestic (Chabot, 2021). Duijm and Schoenmaker (2021) analyze the proportion of domestic and European assets relative to total assets for a panel of the 61 largest European banks. The data was hand-collected as information about the distribution of assets between domestic and non-domestic markets is not readily available. Their results for major European countries are summarized in Table 12 in Appendix. 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".

In addition, in the ECB Occasional Paper No 281 on economy-wide climate stress test, Alogoskoufis et al. (2021) find that "across countries, banks have a strong home bias, giving loans predominantly to domestic rather than foreign firms (...) In all countries, with the exception of Ireland and Luxembourg, 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." Hence, in the absence of information on the geographical distribution of assets and liabilities by each financial institution, national climate indices are relevant climate indicators to capture not all but most of the exposure to climate risks.

We used data from official national meteorological services (Table 13 in the Appendix). Data was cleaned when required so that there are no missing data or discontinuities arising from changes in weather stations (Auffhammer et al., 2013; Auffhammer, 2018). 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), each country index is the weighted aggregate climate data of regional stations using a fixed set of population weights. The concept in creating a country climate index for economic or financial modeling is to reproduce the average climate conditions experienced by economic actors in the considered area, not the average climate conditions of the geographical area. To avoid any bias in the calculation of climate anomalies measured as the difference between observed climate conditions and their 30-year average (1991-2020), the trend was taken into account. Climate anomaly indices are calculated following Baede (2001) and Burke et al. (2009)².

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 localisation, and their consequences, and the countries covered. We reviewed four of the most complete databases: BD Catnat, Munich Re, Swiss Re, and CRED³. Most of these databases are created for the insurance sector. As a result, they tend to over-represent events occurring in developed countries where the insurance penetration rate is high, which for the purposes of our study in the EU is not a limitation. A comparison of the databases over the period 2001-2021 indicates that the total estimated damages are relatively comparable between the 4 databases: \$3,797 billion for BD Catnat, compared to \$3,752 for Munich Re, \$3,604 for Swiss Re, and \$3,066 for CRED. In terms of number of events and completeness, we found BD Catnat to be the most exhaustive, with 18,080 events compared to 16,294, 3,218 and 7,278 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 (Table 2). In addition, three intensity measures are provided for each event: the severity (SEV); the human cost covering the number of victims, deaths, evacuees, etc. (HUM); and the material cost covering the estimated damage to buildings, infrastructure,

² The complete process to transform daily temperature and precipitation data into monthly, quarterly, or annual temperature and precipitation anomaly index is developed in Bertrand et al. (2015) and Bertrand and Parnaudeau (2017).

³ 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.

and other local, regional, national or international material consequences (MAT).

4.3.2. Network Interconnectedness Variables

A network consists of a set of financial institutions (nodes) and a set of relationships (edges) between them. A network is generally built on the basis of a bilateral exposure matrix (BEM) between banks, on which an adjacency matrix is calculated (Co-Pierre, 2013). We use an approach based on correlation filters. This approach allows us to filter the networks and to keep only the relationships for which the common exposure (correlation) between individuals is higher than a specific threshold. Once the network is constructed, it is possible to identify the financial institutions that play an important role in terms of interconnections in this network.

To compute climate network measures, we follow Chabot (2021) who developed a prominence analysis focused on edge attributes. The methodology starts by calculating the clustering coefficient (C) and the average path length (L), which are defined as follows (Bullmore and Sporns, 2009; Telesford et al., 2011):

$$C = \frac{2e_i}{d_i(d_i-1)}; \quad L = \frac{1}{n(n-1)} \sum_{i \neq j} P_{ij} \quad (2)$$

where C is the proportion of edges e_i between the neighbors of a node i relative to the total number of possible edges d_i between these neighbors. High clustering implies specialisation between nodes, which means that the financial institutions concerned are highly interconnected. L is the average path length and n is the number of nodes in the network. The average path length is calculated as the average of the shortest distance between all possible pairs. P_{ij} is the shortest path between i and j . It equals zero if j cannot be reached from i . Small values of L imply that information easily spreads throughout the financial institutions in the networks. The next step is to compute Closeness (CL_i) and Betweenness (Bt_i) measures that we use in this paper (Bech and Atalay, 2008)⁴. They are defined as follows:

$$CL_i = \left(\sum_{j=1}^g ds_{ij} \right)^{-1}; \quad Bt_i = \frac{\sum_{(j,k \neq i; j < k)} P_{jk}(i)}{P_{jk}} \quad (3)$$

⁴ see also Boss et al. (2004), Soramäki et al. (2007), Embree and Roberts (2009), Gómez et al. (2013), Minoiu and Reyes (2013), Langfield et al. (2014), Silva et al. (2016), Aldasoro et al. (2017), Berndsen et al. (2018), Hasan et al. (2018), Houston et al. (2018), Lozano and Cazalda-Infante (2018), Silva and Souza (2017), and Brunetti et al. (2015).

where ds_{ij} is the distance between individual i and the other individuals j in the network, $P_{jk}(i)$ is the shortest path between j and k that contain node i , while P_{jk} is the shortest path between j and k .

Closeness centrality is the inverse of the sum of all the distances ds between node (financial institution) i and the other nodes (financial institutions) j in the network. A financial institution (node) with a high level of closeness therefore has a central location in the network with respect to the considered climate risk. The higher the Closeness centrality, the more the institution is located at the heart of the network of relations, the more important its role in the network is. In other words, the institution characterized by a high Closeness centrality is connected to many institutions and the distance by which it is connected is short.

Unlike Closeness centrality, which focuses on measuring observed distances, Betweenness is about triangles of relationships. Betweenness measures the extent to which a node sits between pairs of other nodes such that a path between the other nodes has to go through that node. A financial institution (node) with a high betweenness is prominent because it is in a position such that risk predominantly goes through this financial institution. The more an institution is an inevitable node, and the shorter the path that connects it to the other institutions in these relationships, the more influential the institution is. The role of this institution in the network becomes more than a simple intermediary, but that of an institution capable of exercising a strong influence over the exchanges that take place within the network.

We calculate CL and BT of each financial institution i in the networks of relationships resulting from each variable of physical risks, namely temperature and precipitation anomalies ($ANOT$ and $ANOP$), the three categories of extreme climate events (HYD , CLI , and MET). So, for instance, CL_{HYD} , BT_{HYD_i} are respectively the Closeness and Betweenness of financial institution i with respect to HYD that relates financial institution i .

4.3.3. Control Variables

The economic variables we use are the traditional determinants of financial stability identified in the literature. Following Caccioli et al. (2013), Brunetti et al. (2015), Kanno (2015), Liu et al. (2015), and Paltalidis et al. (2015), 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). We also calculate interconnectedness variables applied to the price (PX) and inter-bank assets (ITBA) for control purposes.

4.3.4. Econometric Model

The general model for measuring the influence of climate risks on the riskiness of each financial institution follows:

$$\text{FSind}_{it} = \alpha_i + \beta_i \text{Control}_{it} + \gamma_i \text{Climate}_{it} + \delta_i \text{Networks}_{it} + \theta_i \text{GHG}_{it} + \epsilon_{it} \quad (4)$$

where FSind_{it} is an individual Financial Stability measure (successively Z and DP). Control_{it} are asset prices (PX), the 3-month money market rate (3M), real GDP (RGDP), interbank assets (ITBA). The Climate_{it} variables are transition, chronic, and acute climate variables (GHG, ANOT, ANOP, CLI, HYD, MET, SEV, HUM, and MAT). Network_{it} are the network measures Closeness (CL) and Betweenness (BT) applied to ANOT, ANOP, HYD, CLI, and MET. α_i is a constant and ϵ_{it} is the perturbation term. Models 1 measure the influence of control variables. Models 2 measure the influence of physical climate risks (anomalies and number of extreme events). Models 3 measure the influence of transition risks. Models 4 measure the influence of physical climate risks (anomalies and severity of extreme events). Models 5 measure the influence of control variables and climate network measures.

The general model for measuring the influence of climate risks on the financial stability follows:

$$\text{FSeur}_{it} = \alpha_i + \beta_i \text{Control}_{it} + \gamma_i \text{Climate}_{it} + \delta_i \text{Networks}_{it} + \theta_i \text{GHG}_{it} + \epsilon_{it} \quad (5)$$

where FSeur_{it} is a Eurozone Financial Stability measure (successively BFC and V). Control_{it} are asset prices (PX), the 3-month money market rate (3M), real GDP (RGDP), interbank assets (ITBA). The Climate_{it} variables are transition, chronic, and acute climate variables (GHG, ANOT, ANOP, CLI, HYD, MET, SEV, HUM, and MAT). Networks_{it} are the network measures Closeness (CL) and Betweenness (BT) applied to ANOT, ANOP, HYD, CLI, and MET. α_i is a constant and ϵ_{it} is the perturbation term. Models 1* measure the influence of control variables. Models 2* measure the influence of physical climate risks. Models 3*

measure the influence of transition risks. Models 4* measure the influence of physical climate risks. Models 5* measure the influence of control variables and climate network measures.

5. Results

This section presents the descriptive statistics of our databases and discusses the results of the influence of climate risks on financial stability.

5.1. Descriptive statistics and Correlation Analysis

While the descriptive statistics of the financial data do not call for particular comments, the variables relating to physical and climatic risks provide some insights. We first focus on chronic risk variables, i.e., those that describe the evolution of climate anomalies often referred to as climate variability. The average temperature anomaly of the last decade (2011-2020) is 0.39°C higher than the first decade (2001-2010). From one decade to the next, the standard deviation of temperature anomalies increased by almost 50%, from 0.32°C to 0.48°C. Both statistics confirm the rising temperatures due to climate change and the increased variability. Average precipitation over the same periods however did not exhibit any trend or significant change in the standard deviation. We then focus on acute risk variables, i.e., extreme events. Over the same periods, 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 categorised as meteorological were the most frequent (54%), followed by climatic events (29%) and hydrological events (17%). A summary of the descriptive statistics for the climate variables is displayed in Table 3.

A correlation analysis between the financial stability variables and the set of explanatory variables is then carried out. In particular, we test the correlation of the physical climate risk variables (Table 4) and the climate interconnectedness variables (Table 5) with financial stability. We note the remarkable fact that some of the correlations between financial stability and climate interconnectedness variables are higher than those with physical climate risk variables, which tends to confirm the existence of a phenomenon of amplification of climate risks in the network of financial

Table 2: List and description of variables

Abbrev.	Variable	Description	Frequency
Z	Z-score	Measure of financial stability of each financial institution	Annual
DP	Default Probability	Measure of default probability of each financial institution	Daily
BFC	Financial Conditions	Measure of overall level of financial stress in the euro area based on credit availability estimated by Bloomberg	Daily
V	Volatility	Measure of overall level of financial stress measured by Vstox	Daily
RGDP	Real GDP	Real Gross Domestic Product per country	Quarterly
3M	Money market rate	3-month money market rate	Daily
PX	Asset Price	Daily closing price of each financial institution	Daily
ITBA	Interbank Assets	Interbank assets of each financial institution	Annual
NPA	Non-Performing Assets	Non-performing assets of each financial institution	Annual
T1	Tier-1	Tier 1 Capital of each financial institution	Annual
CDS	CDS 5-year	Credit Default Swap 5-year price of each financial institution	Daily
ECBXLIQ	ECB Liquidity	ECB Eurozone Excess Liquidity	Daily
GHG	Emissions	Level of GHG emissions	Annual
ANOT	Temperature Anomaly	Average difference between observed temperatures and their 30-year average	Daily
ANOP	Precipitation Anomaly	Average difference between observed precipitations and their 30-year average	Daily
HYD	Hydrological	Number of Flooding and mudflow events	Annual
CLI	Climatological	Number of Forest fires, coldwaves, heatwaves, and droughts	Annual
MET	Meteorological	Number of cyclones, storms, hail, tornadoes, waterspouts, blizzards, avalanches, and freezing rain	Annual
SEV	Severity	Scale from 0 to 6 ranging from no damage to cataclysm	Annual

Table 2 (Continued): List and description of variables

Abbrev.	Variable	Description	Frequency
HUM	Human	Number of people who were evacuated, injured, homeless, or killed	Annual
MAT	Materiality	Damage to buildings, infrastructure, and economic impact	Annual
BT_X, i	Climate Betweenness	Network measure of the importance of a financial institution i in a network of correlations based on X ; X is successively ANOT, ANOP, HYD, CLI, and MET.	Annual
CL_X, i	Climate Closeness	Network measure of central financial institutions i in a network of correlations based on X ; X is successively ANOT, ANOP, HYD, CLI, and MET.	Annual

Z,DP, BFC, and V are the dependent variables; RGDP, 3M, PX, ITBA, NPA, T1, CDS, and ECBXLIQ are control variables; GHG is a transition risk variable; ANOT and ANOP are chronic climate risk variables; HYD, CLI, MET, SEV, HUM, and MAT are acute climate risk variables; BT and CL are interconnectedness variables. Data are annualized when used in the models. All variables are stationary except for ECBXLIQ which is expressed in first difference.

Table 3: Descriptive Statistics on Climate Variables (2000-2021)

	ANOT	ANOP	HYD	CLI	MET	SEV	HUM	MAT	GHG
Mean	.18	1.00	2.46	3.83	8.64	1287	14.81	20.26	2057
Median	.23	.99	1	0	4	110	9	9	39.55
Maximum	1.73	1.33	19	74	66	54386	95	197	693606
Minimum	-1.96	.62	0	0	0	0	0	0	.06
Std. Dev.	.52	.10	3.43	9.31	13.38	4481	20.41	30.94	36755
Observations	2882	2882	2751	2751	2751	2751	2751	2751	2356

institutions (Dafermos et al., 2018). For instance, the correlation between DP and interconnectedness climate variables ranges from -.0867 to +.1389, while that of climate variables falls within the narrow range of -.0081 and +.0388. Similarly, the correlation between BFC and climate interconnectedness in absolute value reaches .2225 for closeness related to climatic extreme events (CL_{CLI}) and .1333 for betweenness related to meteorological extreme events (BT_{MET}), while the correlation between BFC and physical climate variables does not exceed -.0854 (ANOP) and +.0634 (CLI).

Table 4: Correlation - Financial Stability and Climate Variables

	Z	DP	BFC	V
ANOT	-.0377	.0228	-.0162	.0459
ANOP	-.0089	-.0081	-.0854	.2250
HYD	-.0781	.0388	-.0578	.1141
CLI	-.0470	.0262	.0634	-.0749
MET	-.0743	-.0084	.0147	-.0457
SEV	-.0108	.0115	.0212	.0377
HUM	-.0820	.0190	.0260	-.0364
MAT	-.0699	.0370	.0278	-.0447

Z and DP are measured for each financial institution. Z is the annual Z-score and DP the probability of Default estimated by Bloomberg. BFC and V are Eurozone measures of financial conditions and volatility. ANOT, and ANOP are chronic risks, and CLI, HYD, MET, SEV, HUM, MAT are acute climate variables.

Table 5 also highlights a second remarkable result, namely that the correlation levels between the financial interconnectedness variables and some of the climate interconnectedness variables are of the same order of magnitude. As an example, the correlation between DP and the betweenness of climatic extreme events (BT_{MET}) is $+.1389$, compared to the correlation between DP and the betweenness of stock prices (BT_{PX}) of $+.1259$. Similarly, the correlation between BFC and the climate interconnectedness variables of extreme events HYD, CLI, and MET is overall higher in absolute value than that with the interconnectedness variables of PX and ITB financial variables.

5.2. Graphical Display of Climate Interconnectedness

Due to the large number of climate variables (8 in total between climate anomalies and extreme events measured by their frequency and cost), we cannot display all the climate networks in this paper. However, the influence of each climate interconnectedness variable will be analyzed in the following section on panel models. In this section, we illustrate the graphical representation of financial institutions interconnections related to temperature anomalies, as temperature is the most extensively researched climate variable in the academic literature and the one that captures attention in the Paris agreements. Based on the descriptive analysis that revealed an evolution of climate variability between the last two

Table 5: Correlation - Financial Stability and Interconnectedness (Financial and Climate)

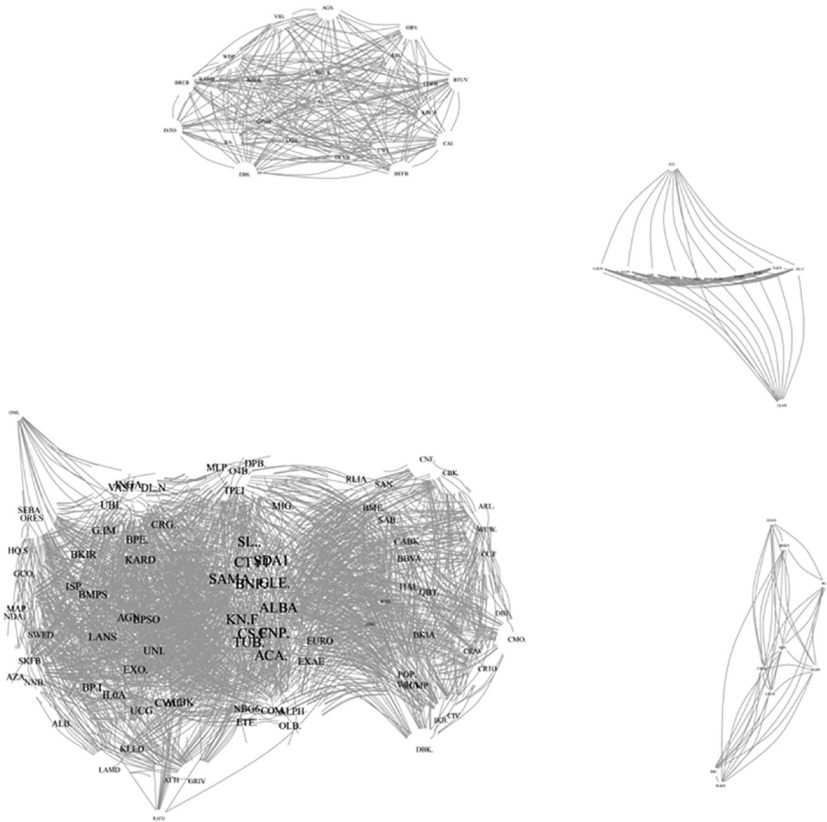
	Z	DP	BFC	V
BT_{HYD}	-.0147	-.0867	-.0402	.0442
BT_{CLI}	-.0440	-.0491	-.1122	-.0125
BT_{MET}	-.0387	.1389	-.1333	.0153
CL_{HYD}	-.0063	-.0411	-.1512	.0041
CL_{CLI}	-.0019	-.04698	-.2225	.0440
CL_{MET}	-.0112	-.0371	-.1182	-.0173
BT_{PX}	-.1944	.1259	.0347	-.0885
BT_{ITB}	-.1156	.0749	.0659	-.0577
CL_{PX}	.2142	-.1744	.1127	-.0836
CL_{ITB}	.0565	-.0982	.0462	-.0575

Z and DP are measured for each financial institution. Z is the annual Z-score and DP the probability of Default estimated by Bloomberg. BFC and V are Eurozone measures of financial conditions and volatility. BT and CL stand for Betweenness and Closeness centrality. ANOT, and ANOP are chronic risks, and CLI, HYD, MET, SEV, HUM, MAT are acute climate variables. PX is the annual average closing price of each financial institution. ITBA is the interbank asset value of each financial institution.

decades, we produced two network visualizations related to temperature anomalies, one for the period 2001 to 2010 (Figure 2), and a second one that covers 2011 to 2020 (Figure 3). To facilitate discussion of the evolution of the network between the two decades, we also propose a schematic representation (Figure 4), that provides the names of the financial institutions instead of their mnemonic codes, keeping only the main institutions for readability reasons.

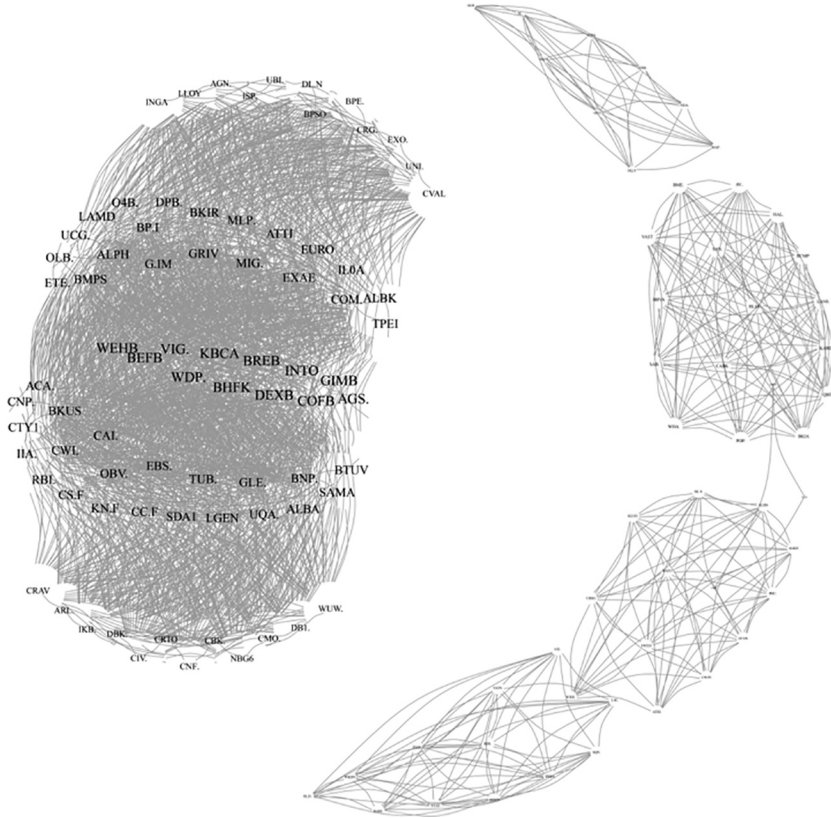
In the first decade (2001-2010), the network that represents the most important relationships of European financial institutions consisted of four distinct and unrelated groups. The first group at the bottom left of Figure 2 and Figure 4 gathers the largest number of institutions and constitutes a dense core with a high degree of interconnectedness and short average distances that favor a faster propagation of potential shocks within this group of interconnected institutions. At the center of the group, French financial institutions (Crédit Agricole, Natixis, Société Générale and insurers like Axa or CNP) occupy a predominant position. Around the French financial institutions evolve two groups of financial institutions, mostly Italian such as Unicredit or Credito Valtelinese on the left, and Spanish such as BBVA, Caixa or Santander on the right. On

Figure 2: Temperature Anomalies Interconnectedness 2001-2010, edge attr. 60%



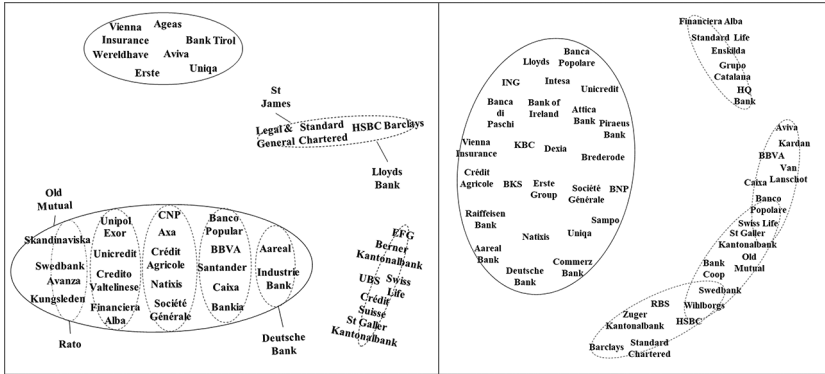
either side of this core, there are predominantly Swedish institutions such as Skandinaviska or Swedbank on the left, and predominantly German institutions such as IndustrieBank or Deutsche Bank on the right, with the latter preferentially attached to German institutions. A second, dense and isolated core is made up mainly of insurers (Aviva, Ageas, Vienna Insurance, Uniqa) and some banks (Dexia, KBC). A third isolated group, less dense in terms of nodes and relationships, is made up almost exclusively of financial institutions from the United Kingdom, with two preferential attachments to St James Place on the one hand and Lloyds Bank on the other. Finally, the network representation displays a fourth group,

Figure 3: Temperature Anomalies Interconnectedness 2011-2020, edge attr. 60%



composed mainly of Swiss financial institutions, banks and insurers, such as UBS, Cr dit Suisse, or Swiss Life. During this first decade, we note that the climate network of temperature anomalies, and more generally the climate networks we have studied, highlight privileged positioning and connections between financial institutions whose main activities are linked to the country in which they are incorporated or listed. Possible explanations include the slowness of the effective opening of a true European market, the legacy of local banking habits and practices that have led to a very active presence of each institution in its domestic market, for the main benefit of domestic clients, who were themselves mostly exposed to domestic climate risks.

Figure 4: Schematic evolution of networks related to temperature anomalies from one decade (2001-2010, left hand side) to the next (2011-2020, right hand side)



In the second decade (2011-2020), the network has evolved considerably. It still has one large group of institutions, but now has five groups in total that are closer to each other, three of which are interconnected (Figure 3 and right hand side diagram of Figure 4). The main group of financial institutions is larger. The position and the connections of each institution in the group are less influenced by the country of origin. The configuration of the network is such that a temperature shock could propagate to a much larger number of institutions, either within the main group of financial institutions or to institutions belonging to one of the three interconnected groups. In the following section, we use panel models to test the influence on financial stability of all interconnectedness variables of the climate networks (i.e., betweenness and closeness).

5.3. Panel Analysis

In this section, we present the estimates of models 1 (1*) to 5 (5*), described in section 4.3.4, which analyse the influence of climate risks and climate networks on the risk of each financial institution, measured as the Z-score (Z) and the 5-year probability of default (DP), and on the financial stability of the system, measured as the Bloomberg Financial Conditions index (BFC) and the volatility of the markets (V). Models 1 (1*) to 5 (5*) test successively the traditional financial explanatory variables, climate

variables, greenhouse gas emissions, and climate interconnectedness variables. The results are summarised in tables 6, 7, and 8.

5.3.1. Financial Stability and Climate Risks

We verify that the traditional financial variables PX (Brunetti et al., 2015), 3M, ITBA, and T1 (Battiston et al., 2012; Tonzer, 2015; Embree and Roberts, 2009; Paltalidis et al., 2015) have a significant influence on the financial stability of each institution measured by Z and DP (Models 1 in Table 6 and Models 1* in Table 7). In line with the literature, most financial variables have a significant influence on both Z and DP at the .01 level, with the exception of interbank assets which only affects DP but not Z. As we add climate variables to the models, we find that both temperature and precipitation anomalies affect Z, a result consistent with previous findings on temperature (Deschênes and Greenstone, 2007; Dell et al., 2012; Burke and Hsiang, 2015; Colacito et al., 2019; Newell et al., 2021). The only extreme event category that has a significant influence on Z and DP is MET, i.e., events such as storms, hurricanes, waterspouts, and thunderstorms. These events tend to involve significant human and material costs, although our analysis shows that only human costs (HUM) significantly influence both Z and DP. As we look at the transition risk, we find that GHG emissions only marginally negatively affect Z (at the .1 level) but does not significantly influence DP, a result that may be explained by the fact that the financial system's exposure to transition risk has hardly changed. In a context where corporate emissions have declined, the exposure of euro area banks to the largest corporate issuers has remained broadly stable (ECB, 2022).

We now focus on the financial stability of the system measured by BFC and V. We find that financial variables do not significantly influence BFC and V (Models 1* in Table 7). However, the influence of some of the financial variables (PX, 3M, RGDP) become significant at the .01 level for both BFC and V as we add climate variables to the models. Models 2* that consider the potential influence of both chronic and extreme climate variables on financial stability show that temperature anomalies, and extreme events such as floods or mudslides (HYD) very significantly affect BFC and V. In the case of V, there is also a significant influence of events such as heat waves, forest fires, or cold waves (CLI). This is consistent with Burke and Hsiang (2015) who showed that agricultural and industrial production is penalized by a rise in temperature in

both rich and poor countries. It is also in line with Kahn et al. (2021) and Colacito et al. (2019) who found that temperature shocks and increased temperatures variability has a negative impact on economic growth. Over the last two decades in Europe, the 2003 heat wave was the first significant temperature-related severe event. It caused a very significant excess of deaths and had important economic consequences. Miller et al. (2021) estimate that the 2003 heat wave cost 35 billion euros (1.7% of GDP) in France alone. In recent years, both climate variability and the number of hot days (5°C above normal temperatures in summer months) have continued to increase. The 2019 European summer heatwaves was in fact considered the world's most lethal climate disaster, specifically in France, Belgium, and the Netherlands with over 2,500 deaths (CRED, 2020). Models 4*, which consider the cost of extreme events, confirm a very significant influence of temperature. In addition, we find that precipitation anomalies and the severity of extreme events both affect financial stability (BFC and V). This is an important result when considering the importance of physical weather risks in Europe in 2021, with major floods, mudslides, storms and fires in Germany, France, Belgium, Italy and Greece, and the hottest July on record disrupting business activity, directly affecting business and household assets, and thus indirectly the profitability of banks and insurers (Arnold, 2021; Bernard and Smith, 2021).

5.3.2. Financial Stability and Climate Interconnectedness

Models 5 and 5* test the influence of the climate interconnectedness variables on the risk of individual European financial institutions and on the European financial system as a whole (Table 8).

First, we consider the influence of climate interconnectedness on individual financial institutions (Z and DP) and investigate the networks related to chronic climate risks. We find that the interconnectedness variables of the networks of temperature and precipitation anomalies have a very significant influence. When looking at the temperature anomalies network, we find that the interconnectedness measures betweenness and closeness influence Z and DP at the .01 level. This means that both the position of a financial institution in the network (closeness) and its importance in the network (betweenness) are to be considered in the propagation of a temperature shock. This is an important result when considering the expected rising variability of temperature induced by climate change and

Table 6: Climate Risks and Financial Stability (Z and DP)

Model	Z			DP			Model	Z	DP
	1	2	3	1	2	3		4	4
PX	.09*** (2.73)	.09*** (3.18)	.91* (1.56)	.02*** (2.42)	-.02*** (-2.53)	.33 (.82)	PX	.09*** (3.18)	-.02*** (-3.63)
3M	.16*** (4.23)	.02*** (4.73)	2.47** (2.64)	-.03*** (-4.03)	.004*** (3.70)	.24 (.54)	3M	.019*** (4.75)	.004*** (3.63)
RGDP	.01 (.33)	.06 (.24)	1.04*** (2.28)	.006 (.33)	.006 (.52)	-.14 (-1.02)	RGDP	.006 (.26)	.005 (.44)
ITBA	.13 (.37)	-1.37*** (-2.35)	-1.52*** (-1.82)	-.32** (-1.87)	-.05 (-.27)	.07 (.66)	ITBA	-1.24*** (-2.20)	-.16 (-.81)
NPA	-2.90*** (-6.24)	-2.78*** (-3.25)	-1.42 (-.91)	.93*** (3.60)	.89*** (2.32)	1.30 (1.20)	NPA	-2.83*** (-3.38)	.90*** (2.35)
T1	1.30*** (3.37)	1.52*** (4.20)	1.51*** (3.52)	-.48*** (-3.38)	-.53*** (-3.25)	-.30** (-1.81)	T1	1.52*** (4.18)	-.52*** (-.78)
ANOT		.03*** (2.04)			-.004 (-.67)		ANOT	.03*** (2.11)	-.005 (-.78)
ANOP		.10*** (2.21)			-.037* (-1.54)		ANOP	.08** (1.86)	-.03* (-1.41)
CLI		.0007 (1.04)			.0009 (.22)		SEV	1.03 (.73)	2.05 (.44)
HYD		-.001 (-.52)			.004 (.54)		HUM	.001*** (2.10)	.004*** (2.05)
MET		.001*** (2.40)			-.0004*** (-2.37)		MAT	-.0003 (-.86)	.002 (1.30)
GHG			-9.28* (-1.36)			-3.80 (-.84)			
c	.03** (1.67)	-.11*** (-1.97)	.93** (2.86)	.04*** (2.38)	-.08*** (3.08)	-.02 (-.19)	c	-.09** (-1.67)	.08*** (2.94)
F-test	12.15***	8.16***	3.93***	3.93***	4.32***	2.67***	F-test	8.09***	4.26***
R-sq.	.30	.42	.48	.22	.37	.41	R-sq.	.43	.27
Hausman	33.90***	42.85***	25.91***	22.11***	28.85***	19.64***	Hausman	40.82***	30.58***
SE Clust.	No	No	No	No	No	No	SE Clust.	No	No

Z and DP are measured for each financial institution. Z is the annual Z-score and DP the probability of Default estimated by Bloomberg. **Model 1:** Financial stability and PX, 3M, RGDP, ITBA, NPA, and T1 as control variables; **Model 2:** Financial stability, control variables, ANOT, and ANOP as chronic risks and CLI, HYD, and MET as the number of acute climate events; **Model 3:** Financial stability, control variables, and GHG; **Model 4:** Financial stability, control variables, chronic risks, and SEV, HUM, and MAT as the severity and cost of acute climate events. 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). ***: significant at the .01 level; **: significant at the .05 level; *: significant at the .10 level.

Table 7: Climate Risks and Financial Stability (BFC and V)

Model	BFC			V			Model	BFC V	
	1*	2*	3*	1*	2*	3*		4*	4*
PX	1.43 (1.39)	1.44*** (2.49)	3.49** (1.75)	-4.56 (-1.38)	-4.79*** (-3.07)	6.01 (1.06)	PX	1.42**** (2.58)	-4.58*** (-3.29)
3M	-6.09 (-.14)	-.62*** (-15.10)	-5.12*** (-6.38)	12.84 (.81)	1.37*** (10.42)	5.74*** (6.84)	3M	-.64*** (-17.39)	1.47*** (10.20)
RGDP	.90 (.51)	1.02*** (5.69)	.31*** (1.47)	-10.32 (-1.36)	10.14*** (16.07)	1.82*** (8.47)	RGDP	1.10*** (7.72)	10.67*** (19.37)
ITBA	-2.61 (-.30)	1.24 (.15)	1.79 (.62)	1.33 (.04)	33.39 (1.39)	-3.63 (-.36)	ITBA	1.74 (.21)	22.32 (.91)
NPA	-5.43 (-.87)	4.06 (1.05)	-7.96*** (-3.26)	2.13 (1.10)	13.36 (1.08)	2.61*** (2.56)	NPA	-6.43** (-1.71)	28.19** (2.12)
T1	.69 (.84)	1.55 (.95)	2.63* (1.47)	8.82 (.77)	14.47*** (2.62)	-5.96 (-.88)	T1	1.15 (.69)	9.31* (1.55)
ANOT		-.37*** (-5.10)			-2.42*** (-9.02)		ANOT	.35*** (-4.61)	-2.40*** (-8.13)
ANOP		.74 (1.09)			4.13 (1.29)		ANOP	.05* (.07)	8.03*** (2.57)
CLI		.01 (1.13)			-1.12*** (-2.44)		SEV	6.47*** (3.75)	-.0003*** (-5.37)
HYD		-.07** (-2.12)			-.44*** (-4.55)		HUM	.003 (.30)	.026 (.81)
MET		.007 (.64)			-.04 (-1.32)		MAT	-.002 (-.86)	-.0019 (-.91)
GHG			-2.22 (-.69)			-3.71 (-.28)			
c	-.56 (-1.41)	-1.17*** (-1.61)	-16.79*** (-8.05)	22.82*** (13.94)	17.79*** (5.50)	197.69*** (8.97)	c	-.61* (-.80)	14.47*** (4.57)
F-test	16.77***	10.11***	1.09***	10.79***	9.59***	6.36***	F-test	10.05***	8.96***
R-sq.	.44	.45	.60	.19	.45	.52	R-sq.	.45	.44
Hausman	41.11***	47.95***	8.26**	16.04***	24.95***	7.64**	Hausman	45.94***	22.27***
SE Clust.	No	No	No	No	No	No	SE Clust.	No	No

BFC and V are Eurozone measures of financial conditions and volatility. **Model 1***: Financial stability and PX, 3M, RGDP, ITBA, NPA, and T1 as control variables; **Model 2***: Financial stability, control variables, ANOT, and ANOP as chronic risks and CLI, HYD, and MET as the number of acute climate events; **Model 3***: Financial stability, control variables, and GHG ; **Model 4***: Financial stability, control variables, chronic risks, and SEV, HUM, and MAT as the severity and cost of acute climate events. ***: significant at the .01 level; **: significant at the .05 level; *: significant at the .10 level. 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).

its increasing impact on the economy. For the precipitation anomalies network, we also find betweenness and closeness to influence respectively DP and Z at the .01 level. We next investigate the networks related to extreme events. We find that Z and DP are influenced by betweenness and closeness of CLI and HYD networks, i.e., flooding, heatwaves, coldwaves, droughts, which are among the most frequent types of extreme events in Europe. These results confirm that not only are financial institutions indirectly affected by the climate exposures of the assets in which they are invested, but they are also affected by physical climate risk of other financial institutions within the European financial system.

Next, we analyse the influence of climate interconnectedness on the financial stability of the whole European financial system (BFC and V). We start with temperature and precipitation anomalies. We find that the financial stability of the system, whether measured by BFC or V, is not significantly influenced by betweenness, but strongly influenced by closeness, in other words the centrality of the position in the network. This implies that financial institutions such as KBC, Crédit Agricole, Vienna Insurance, Dexia, Société Générale, Attica Bank are potentially important nodes in the event of temperature or precipitation shocks (Figure 4). Similarly, in the parts of the network made up of the three groups of financial institutions, HSBC, Swedbank, Swiss Life, and Banco Popolare are institutions that could contribute significantly to the propagation of a climate shock. If we now consider the networks of extreme events, we find that financial stability, again whether measured as BFC or V, is affected at the .01 level by both the position (Closeness) and the importance (Betweenness) of financial institutions in their network for all categories of extreme events, i.e., CLI, MET and HYD. This again is a very important result that needs to be considered in the context of systemic risk and climate-related regulatory and supervisory practices.

To date, there is no binding climate-related prudential regulation with respect to capital requirements (Feridun and Gungor, 2020). In the UK, the Prudential Regulation Authority (PRA) published supervisory expectations for banks and insurers asking them to consider how they can assess the climate-related financial risks associated with their clients and counterparties (Bank of England, 2019). Since, the Bank of England's Systemic Risk Survey which is conducted on a bi-annual basis showed that 24% of respondents cited climate risk as a source of risk to the UK financial system, an increase of 21 percentage points from the 2019 survey.

Table 8: Financial Stability and Climate Interconnectedness

Model 5 5*	Z	DP	BFC	V
PX	.03*	.01*	1.72***	−5.92***
	(1.60)	(1.43)	(4.58)	(−4.31)
3M	.02***	−.008*	−.96***	2.87***
	(1.99)	(−1.46)	(−16.27)	(12.53)
RGDP	.14***	−.05*	.71***	−9.03***
	(2.75)	(−1.56)	(4.62)	(−8.82)
ITBA	.62	−.56***	−9.68	39.07*
	(1.14)	(−2.35)	(−1.45)	(1.47)
NPA	−1.84***	.53*	2.60	−2.97
	(−2.70)	(1.51)	(1.20)	(−.54)
T1	1.14***	−.33***	.21	−6.35
	(4.80)	(−2.86)	(.16)	(−1.18)
BT_{ANOT}	−.0005***	.001***	−.0019	.01
	(−3.98)	(2.62)	(−.31)	(.48)
BT_{ANOP}	.0001	−.0001***	−.0002	9.59**
	(1.03)	(−2.07)	(−.41)	(.04)
BT_{CLI}	.001*	−.0005*	−.01***	.04***
	(1.30)	(−1.55)	(3.16)	(3.28)
BT_{HYD}	.001***	−.0007***	−.004	.05***
	(2.57)	(−2.64)	(−1.06)	(2.14)
BT_{MET}	−2.29	.0002*	−.002***	.01***
	(−.08)	(1.64)	(−3.11)	(3.32)
CL_{ANOT}	83.81***	−18.22***	1183.94***	−3749.57***
	(4.32)	(−2.45)	(18.28)	(−16.12)
CL_{ANOP}	248.34***	−33.77	−1966.32***	9127.43***
	(2.78)	(−1.01)	(−5.80)	(4.72)
CL_{CLI}	−119.35***	19.47*	273.27***	−1360.91***
	(−3.35)	(1.54)	(3.32)	(−3.88)
CL_{HYD}	−133.43***	−9.07	−720.56*	627.56
	(2.11)	(−.51)	(−1.44)	(.33)

Table 8 (Continued): Financial Stability and Climate Interconnectedness

Model 5 5*	Z	DP	BFC	V
<i>CL_{MET}</i>	39.41 (.49)	24.77* (1.37)	1491.18*** (2.34)	−5938.31*** (−2.69)
c	−.12*** (−2.98)	.07*** (4.06)	−.93*** (−10.03)	23.97*** (78.04)
F-test	7.90***	4.15***	21.86***	10.03***
R-sq.	.60	.42	.51	.44
Hausman	57.75***	21.06*	7.12*	5.97**
SE Clust.	No	No	No	No

Model 5 | 5*: FSind (Z and DP), and FSeur (BFC and V) successively as the dependent variable, PX, 3M, RGDP, ITBA, NPA, and T1 as control variables, climate interconnect- edness variables. ***: significant at the .01 level; **: significant at the .05 level; *: significant at the .10 level. 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).

Participants include UK banks, large foreign banks, and insurance companies, for which Charlotte Gerken announced in March 2022 that the PRA is considering assessing whether the current capital framework for insurance companies is "fit for purpose" when it comes to incorporating climate risks. Policy makers and supervisors are gradually considering revising the prudential framework to take full account of the implications of climate-related financial risks for financial stability (Carney et al., 2019; Baranovic et al., 2021). The ECB is continuing its work on incorporating climate-related risks into assessments of financial stability. In particular, it is enhancing its approaches to understanding, monitoring and assessing financial institutions' exposures to transition and physical risks. In the May 2022 Financial Stability Review, the ECB stated that established and recent measures do not clearly indicate a reduction in climate-related risks, but rather reveal the potential for amplification mechanisms arising from the concentration of exposures, correlation between risks, and overlapping portfolios of financial institutions (ECB, 2022). Given that financial institutions' exposure to climate change is mostly indirect, one way to improve their ability to better assess their risk is through better corporate climate-related disclosures. The moves from the UK government, the Securities Exchange Commission, and the International Accounting Standards Board to make TCFD-aligned climate risk

disclosure mandatory is a step in the right direction (TCFD, 2020; IFRS, 2021; Simpson, 2022). Another avenue supported by the ECB is to develop new tools, such as concentration risk measures, to address climate-related risks from a systemic perspective. The database we created, which assigns each institution a dynamic closeness and betweenness value for each type of climate hazard, makes it possible to rank financial institutions, reveal risk concentrations and identify "Climate-SIFIs", i.e., financial institutions that are systemically important with respect to climate risks.

5.4. Robustness

Given that the unusual and substantial economic and financial events of the Great Recession (GR) of 2008 strongly influenced financial stability conditions in the euro area, we examined the robustness of our results. We divided the full sample into three periods, i.e., pre-GR (2000-2006), GR (2007-2008), and post-GR (2010-2021). We also considered two additional GR-related control variables: a liquidity measure (ECBXLIQ), and a credit risk measure (CDS). ECBXLIQ is the ECB Eurozone Excess Liquidity and CDS is the Credit Default Swap 5-year price for each institution for which such security exists. If our results are robust, knowing that climate risk is a separate risk category (ESMA, 2022), then the 2008 crisis, which is a liquidity and credit risk crisis, should not question the influence of climate risks on financial stability. We verified that there are no significant correlations between the measures of risk, financial stability and interconnectedness. We verified that all series of variables are stationary. We also confirmed the absence of endogeneity for all of the regressors in the various considered models.

The estimates of our models in three sub-periods are presented in Table 9 (Financial stability and climate risks) and Table 10 (Financial stability and climate interconnectedness). The segmentation into three sub-periods, one of which is very short (GR), makes it necessary to aggregate the measures of climate interconnections before integrating them into the panel regression models (models 6 and 7, and 6* and 7*). The network effects remain robust from one period to another, which reinforces our results on the influence of climate risks on financial stability.

We then controlled the robustness of the results by considering another measure of financial stability commonly used in the literature,

namely SRISK (Acharya and Yorulmazer, 2008; Browlees and Robert, 2016). Similarly, we verified that all series of variables are stationary. We confirmed the absence of endogeneity (Granger causality tests). The results displayed in Table 11 confirm the influence of the climate variables, particularly in their systemic dimension (models 9 and 10 in Table 11).

6. Conclusion

As the IPCC reports accumulate (IPCC, 2021), awareness of the speed and magnitude of climate change and the need to reduce greenhouse gas emissions is gaining momentum. The transmission channels from the real economy to the financial system and the associated risks are also increasingly better understood (Carney, 2015). The transition away from fossil fuels and the rise in climate variability and extreme events expose firms and the financial institutions that finance them to increasing risks, to the point that regulators have identified climate change as a separate risk category and as a source of systemic risk, with potential severe consequences for financial institutions. The efforts of academics and regulators have so far focused mainly on transition risk, but work on physical risk is still in its early stages while regulators are concerned that physical climate risk may be comparatively more substantial and that potential amplification could arise from risk concentration (ECB, 2021). This study is motivated by the need to close these gaps and develop new approaches and metrics to advance understanding of physical climate risks.

In this paper, we analyze the influence of climate risks both transition and physical on the financial stability in the European financial system. We follow TCFD guidance in defining physical climate risks, which include chronic risks that relate to changes in weather patterns and acute risks that arise from extreme events. Our objective was to explore the influence of climate risks on European financial institutions on the one hand, and on the other hand to investigate the networks and possible risk concentrations related to climate change as they apply to the European financial system. Our methodology is supported by correlation studies, network analyses and panel regressions. To measure the influence of physical risks, we rely on a proprietary database that records the number of extreme events classified by category and their material and human consequences since 2000. To our knowledge, this is one of the first papers

Table 9: Financial Stability and Climate Risks - subperiods

Model 6 6*	2000-2006				2007-2009				2010-2021			
	Z	DP	BFC	V	Z	DP	BFC	V	Z	DP	BFC	V
PX	2.56*** (11.21)	-2.46*** (-5.60)	-4.40 (-.48)	-1.11 (-.52)	5.46 (.12)	-1.79 (-.94)	5.87 (-.41)	-2.39 (-.34)	1.9 (1.22)	-5.44 (-.50)	6.13 (.27)	.004 (.38)
3M	.004 (.37)	.01*** (10.27)	-.83*** (-2.33)	8.65*** (1.05)	.12 (1.53)	.001 (.47)	-4.66*** (-1.83)	14.93*** (1.19)	.03*** (3.54)	.001 (.2)	-2.87*** (-18.66)	8.08*** (11.08)
RGDP	.09 (.65)	-.12*** (-8.85)	7.85*** (2.19)	85.94*** (1.04)	.38 (.53)	.03 (.33)	-74.21*** (-3.30)	27.53*** (2.49)	.10*** (2.28)	-.12*** (-8.85)	3.54*** (5.03)	.91 (.25)
ITBA	-2.12*** (-8.71)	-1.78*** (-3.89)	1.85 (.51)	2.29 (.28)	-6.16 (-.43)	-9.14* (-1.49)	1.55 (.34)	9.32 (.41)	-7.44*** (-2.67)	-1.02*** (-3.09)	2.6 (.51)	3.25 (.14)
NPA	-2.53*** (-6.10)	.03 (.71)	1.31 (1.38)	9.01 (.41)	1.75 (.99)	.06 (.79)	-1.05** (-1.88)	-5.43** (-1.97)	.41 (1.21)	.03* (1.29)	-9.76*** (2.30)	-13.02 (-.63)
T1	1.30*** (5.90)	-.001 (-.03)	4.23 (1.05)	2.13 (.23)	1.67* (1.68)	.01 (.40)	5.55* (1.75)	2.80** (1.80)	.08 (.55)	-.03*** (-2.82)	3.75* (1.43)	3.53 (.23)
ECBXLIQ	9.05*** (6.16)	-1.15*** (-6.36)	.001*** (2.75)	.009*** (9.61)	8.11 (1.04)	1.05 (.31)	.003*** (1.43)	.001*** (1.24)	2.65*** (3.39)	-2.44*** (-2.95)	5.42*** (3.42)	-2.28 (-.02)
CDS	-.003*** (-5.24)	.003*** (4.92)	-1.86 (-.13)	4.29 (1.33)	-.0007 (-1.41)	6.46*** (3.02)	-2.85* (-1.80)	1.30* (1.66)	-.003*** (-3.94)	3.93*** (4.64)	-.001*** (-1.78)	-.003 (-.72)

Table 9 (Continued): Financial Stability and Climate Risks - subperiods

Model 6 6*	2000-2006				2007-2009				2010-2021			
	Z	DP	BFC	V	Z	DP	BFC	V	Z	DP	BFC	V
ANOT	.02*** (2.89)	.003*** (4.13)	2.77 (1.08)	8.61 (.20)	.02 (.21)	.003 (.54)	4.7 (1.28)	-2.57* (-1.43)	-.003 (-.07)	.001*** (1.94)	1.13*** (10.58)	5.52*** (10.53)
ANOP	.49*** (14.21)	.002*** (7.73)	1.94*** (1.98)	-3.96** (-1.72)	.58 (.98)	.01 (.51)	3.45*** (1.81)	1.95*** (2.08)	.015 (.45)	.006* (1.65)	.39 (.65)	1.63 (.53)
CLI	.0004*** (4.21)	7.80*** (6.13)	5.12** (1.74)	-7.42 (-1.10)	.004 (1.06)	.001 (.42)	1.25 (.90)	7.64 (1.11)	.008** (1.84)	9.62*** (1.70)	.01* (1.34)	-.05* (-1.44)
HYD	.03*** (19.10)	.005*** (3.82)	1.16** (2.03)	1.82 (1.38)	.01 (1.22)	.001 (.43)	5.10* (1.58)	-2.82** (-1.77)	-4.18 (-.04)	.001 (1.22)	.01 (.85)	.28*** (2.54)
MET	-.003*** (-10.19)	7.30*** (2.7)	-1.77*** (-2.002)	-2.21 (-1.08)	-.002* (-1.68)	.001*** (2.04)	-2.5 (-.65)	8.69 (.46)	-.007*** (-2.69)	7.43*** (2.05)	.009 (.15)	-.03 (-1.12)
c	-.013* (-31)	.04*** (13.26)	2.81*** (2.31)	.09*** (3.55)	.008*** (1.02)	.52*** (1.26)	1.74** (2.14)	5.88** (-3.58)	.06*** (1.90)	.003*** (1.63)	.58** (1.86)	18.03*** (5.18)
F-test	136.4*** .89	208.6*** .89	5.51*** .79	1.13*** .79	6.09*** .56	8.26*** .61	2.66*** .51	7.46** .48	7.75*** .56	19.53*** .76	63.45*** .81	26.39*** .78

Model 6 | 6*: Risk (Z and DP) and Financial stability (BFC and V) successively as the dependent variable, PX, 3M, RGDP, ITBA, NPA, TI, ECBXLIQ (first difference), and CDS as control variables, ANOT and ANOP as chronic climate variables, and CLI, HYD, and MET as acute climate variables. The segmentation into subperiods follows Chabot (2021). ***, **, * significant at the .01 level; **, * significant at the .05 level; * significant at the .10 level. F-test is a test a joint relevance of the variables in the models. R-squ. is the goodness of fit.

Table 10: Financial Stability and Climate Interconnectedness - subperiods

Model 7 7*	2000-2006				2007-2009				2010-2021			
	Z	DP	BFC	V	Z	DP	BFC	V	Z	DP	BFC	V
PX	.005*** (11.94)	1.26 (.92)	1.75*** (2.64)	2.46 (.56)	.006 (1.21)	4.85** (1.98)	1.58*** (2.34)	-5.30* (-1.51)	5.63*** (1.98)	3.08 (.95)	.003 (.92)	-.002 (-1.14)
3M	.21*** (11.61)	-.08* (-1.52)	-.83*** (-3.03)	8.65*** (4.79)	.08* (1.51)	-6.88 (-.02)	4.66*** (6.67)	14.93*** (4.22)	.02** (1.79)	.0007 (.42)	-2.57*** (-11.01)	6.69*** (5.65)
RGDP	2.42*** (12.15)	-.10* (-1.64)	7.85*** (2.65)	85.94*** (4.43)	.15 (.89)	.04*** (5.71)	74.21*** (3.20)	275.33*** (2.93)	.08 (1.25)	-.02*** (-3.26)	5.40*** (5.19)	2.01 (.38)
ITBA	-3.60*** (-12.84)	1.33* (1.55)	-3.67 (-.88)	8.17 (.03)	-7.94 (-.93)	1.24*** (3.02)	-1.86* (-1.74)	5.51 (.99)	-9.85* (-1.64)	-1.04* (-1.52)	-1.02 (.90)	6.59 (.15)
NPA	-1.69*** (-3.59)	.012 (.08)	7.19 (1.02)	-9.19* (-2.00)	1.4 (.84)	.02 (.25)	-6.76*** (-3.04)	-3.25*** (-3.08)	-.13 (-.28)	.02 (.40)	9.26 (1.32)	-10.87 (-.30)
T1	1.38*** (4.86)	-.03 (-.45)	-4.03 (-.95)	2.92 (1.05)	.16 (.20)	-.01 (-.36)	2.38** (2.19)	1.24*** (2.34)	.45* (1.55)	-.01 (-.55)	2.53 (.59)	-14.34 (.50)
ECBXLJQ	.002*** (11.58)	1.06 (1.39)	.001*** (3.11)	.009*** (3.82)	1.93 (.98)	-2.80*** (-3.01)	.003*** (1.36)	.001*** (1.18)	2.67** (1.81)	-2.59* (-1.54)	6.93*** (3.25)	2.16 (.20)
CDS	-.001* (-2.25)	.002 (.35)	-2.12** (-1.93)	1.58* (2.20)	-.005* (-2.02)	5.07*** (3.31)	-8.85* (-2.19)	-4.37*** (-2.59)	-.003*** (-3.72)	5.85*** (5.89)	-.002** (-1.95)	-.003 (.55)

Table 10 (Continued): Financial Stability and Climate Interconnectedness - subperiods

Model 7 7*	2000-2006					2007-2009					2010-2021				
	Z	DP	BFC	V		Z	DP	BFC	V		Z	DP	BFC	V	
<i>BT_{Climate}</i>	.002*** (12.03)	-8.12 (-1.18)	8.80*** (2.63)	-1.28 (-.58)		-.003* (-1.71)	1.94*** (2.43)	-6.46*** (-2.80)	2.43** (2.05)		.001** (1.45)	-2.21*** (-1.87)	.009 (.65)	-.001* (-1.18)	
<i>CL_{Climate}</i>	-210.56*** (-12.79)	8.60* (1.71)	-6.68*** (-2.73)	1.31 (.82)		-4.88 (-.52)	-.07 (-.18)	3.87*** (3.30)	-1.76*** (-2.94)		271.88** (1.36)	57.81*** (2.54)	824.15 (.77)	-125.85 (-.86)	
c	1.58*** (15.10)	-.03* (-1.10)	2.81*** (1.81)	.09*** (9.76)		1.97** (2.63)	2.61* (1.89)	1.39** (1.85)	1.19*** (3.56)		-.27** (-1.25)	-.06*** (-2.12)	.04 (.01)	37.15* (2.01)	
F-test	87.91*** (15.10)	4.94*** (-1.10)	5.50*** (1.81)	1.39*** (9.76)		1.97*** (2.63)	2.78*** (1.89)	3.07*** (1.85)	8.66*** (3.56)		4.74*** (1.25)	11.72*** (2.12)	2.98*** (.01)	7.54*** (2.01)	
R-sq	.89	.66	.81	.61		.47	.35	.39	.47		.37	.59	.44	.22	

Model 7 | 7*: Risk (Z and DP) and Financial stability (BFC and V) successively as the dependent variable, PX, 3M, RGDP, ITB, NPA, TI, ECBXLIQ (first difference), and CDS as control variables, *BT_{Climate}* and *CL_{Climate}* are the climate interconnectedness variables resulting from the addition of the network measures of ANOT, ANOP, CLI, HYD, and MET. The segmentation into subperiods follows Chabot (2021). ***: significant at the .01 level; **: significant at the .05 level; *: significant at the .10 level. F-test is a test a joint relevance of the variables in the models. R-squ. is the goodness of fit.

Table 11: SRISK as Financial Stability dependent variable

Model 8		Model 9		Model 10	
PX	-.005 (-.92)	PX	-.006 (-.94)	PX	.001 (.15)
3M	-6.98 (-.58)	3M	2.82 (.90)	3M	3.41 (.15)
RGDP	-15.68 (-.22)	RGDP	-99.72 (-.75)	RGDP	-14.08 (-1.19)
ITBA	-.003* (-1.52)	ITBA	-.001 (-.56)	ITBA	-1.95 (-.11)
NPA	9.47 (.96)	NPA	22.25*** (2.29)	NPA	57.65*** (5.94)
T1	-18.82*** (-3.11)	T1	-1.54 (-.18)	T1	-11.96*** (-2.14)
ECBXLIQ	-5.23 (-.06)	ECBXLIQ	-1.54 (-.18)	ECBXLIQ	-5.01 (-.67)
CDS	-.02 (-.66)	CDS	-.05 (-1.09)	BT_{CDS}	1.95 (1.3)
				CL_{CDS}	11.51*** (6.67)
ANOT	-15.64 (-.67)	BT_{ANOT}	-4.65** (-1.82)	BT_{ANOT}	-77.33*** (-7.27)
ANOP	-132.88 (-1.01)	BT_{ANOP}	-.34 (-1.19)	BT_{ANOP}	.52* (1.66)
CLI	-1.10 (-.50)	BT_{CLI}	.35 (.19)	BT_{CLI}	10.11*** (4.30)
HYD	19.17*** (3.37)	BT_{HYD}	4.94*** (2.57)	BT_{HYD}	-28.26*** (-4.35)
MET	-1.43 (-.81)	BT_{MET}	1.81*** (3.04)	BT_{MET}	7.09*** (7.23)
		CL_{ANOT}	61 (.19)	CL_{ANOT}	18.97 (1.35)
		CL_{ANOP}	32.30** (1.74)	CL_{ANOP}	-19.68*** (-3.26)

Table 11 (Continued): SRISK as Financial Stability dependent variable

Model 8		Model 9		Model 10	
c	23.82** (1.70)	CL_{CLI}	-10.97* (-1.65)	CL_{CLI}	-43.46*** (-3.56)
		CL_{HYD}	-26.22* (-1.62)	CL_{HYD}	12.34*** (3.65)
		CL_{MET}	89.71 (.54)	CL_{MET}	12.71*** (5.41)
		c	17.03*** (2.90)	c	-67.65*** (-5.28)
		F-test	4.29***	F-test	5.21***
R-sq	.11	R-sq	.21	R-sq	.42
Hausman test	2.56***	Hausman test	2.14***	Hausman test	5.87***
SE clustering	No	SE clustering	No	SE clustering	No
Model 8: SRISK as the dependent variable, PX, 3M, RGDP, ITBA, NPA, T1, ECBXLIQ, and CDS as control variables, and climate variables; Model 9: SRISK, PX, 3M, RGDP, ITBA, NPA, T1, ECBXLIQ, and CDS as control variables, and climate interconnectedness variables; Model 10: SRISK, PX, 3M, RGDP, ITBA, NPA, T1, ECBXLIQ, and CDS interconnectedness as control variables, and climate interconnectedness variables. ***: significant at the .01 level; **: significant at the .05 level; *: significant at the .10 level. F-test is 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).					

that does not rely on proxies to explore the role of extreme events in financial stability. Our work highlights several important results. First, we find that both chronic and acute physical climate risks significantly influence the risk of European financial institutions as measured by the Z-score and the probability of default. We also show that both chronic and acute climate risks affect financial stability. Second, the comparative analysis of the influence on financial stability of climate variables and climate network interconnection variables shows that there is a phenomenon of amplification of the consequences of climate risks, with their influence on financial stability measured in their networks being greater than their direct influence. This is an important result. Third, another analysis comparing the interconnectedness variables of climate networks with those of conventional financial networks shows that the influence of climate risks is comparable in magnitude to the influence of conventional financial parameters used by regulators to monitor systemic risk. This is

also an important result that confirms the systemic importance of climate risk. Fourth, network analysis based on climate risk categories and the determination of climate interconnectedness variables offer the possibility to identify financial institutions at risk and possible risk concentrations. This is the first time that climate networks constructed from climate and extreme event data have been used to identify the influence of climate risks on the financial stability of institutions and the system in which they operate. Network analysis makes it possible to build an analytical database of interconnectedness characteristics per financial institution, to observe their evolution over time, and to identify among the financial institutions those that should be carefully monitored, either because of their importance in the network or because of their individual exposure to the consequences of climate risks.

One of the limitations of this work, which also leads to the main recommendation, is the lack of standardized information on climate risk provided by banks (Arnold, 2022; Elderson, 2022), which themselves depend on information from the companies in which they are invested. Indeed, while both our work and that of the ECB (ECB, 2021) show that physical risks have a significant influence on financial stability, the results are biased due to the absence of geo-localized information on the amount of assets at risk held by banks. The future Corporate Sustainability Report Directive (CSRD), which aims to standardize extra-financial reporting for better comparability between companies, and to extend the scope of application to more than 50,000 companies in Europe, is an opportunity to create standardized climate risk metrics within the framework of the new CSRD standard ESRS E1 on climate change, which is still in the draft stage. The double materiality, on which the CSRD is based, imposes a fine granular analysis of climate issues as an entry point for the future sustainability report of non-financial companies and, in turn, of the banks that finance them. As such, our analysis contributes to the policy debate on mandatory disclosures and the need to propose standardized climate risk indicators and make climate data available so that companies can estimate their own risks. Given the materiality of the impact of physical climate risks, regulators should initially propose a list of perils so that climate data providers and corporate risk managers can together produce more useful location-based risk information than the current boilerplate disclosures. As a second step, regulators should require banks to rely on this information to produce an accurate, geo-localized statement and

valuation of their climate risk exposures. Finally, prudential rules should incorporate the potential losses associated with chronic and acute climate risks, and incorporate the climate interconnectedness measures highlighted in this work to take into account potential amplification mechanisms. With improved information, future research should provide a better measure of the systemic nature of climate risk.

7. Data availability

Some of the 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, and financial data extracted from Bloomberg to which the authors have access through a subscription from the research organisation with which they are affiliated. The data is available from the corresponding author upon reasonable request, provided that the proprietor of the requested data agrees.

8. Appendix

Table 12: Geographical distribution of assets per country as a percentage of total assets. Adapted from : Duijm and Schoenmaker, (2021).

	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

Figure 5: Correlation between annual temperature anomalies

	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

Table 13: Data Sources for the computation of temperature and precipitations anomalies

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 Meteorologia
Sweden	Swedish Meteorological and Hydrological Institute
Switzerland	MeteoSwiss
UK	Met Office

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