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From flood to fire: is physical climate risk taken into account in banks' residential mortgage rates?

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Abstract

Physical climate risks can have a large regional impact, which can influence mortgage loans' credit risk and should be priced by the lenders. Motivated by the relevance of climate change for financial intermediaries, our paper aims at analysing if physical climate risks are being reflected in residential real estate loan rates of banks. We show that on average banks seem to demand a physical climate risk premium from mortgage borrowers and the premium has increased over recent years. However, there is significant heterogeneity in bank practices. Banks that were identified as "adequately" considering climate risk in the credit risk management by the ECB Banking Supervision charge higher risk premia which have been increasing particularly after the publication of supervisory expectations. In contrast, the lack of risk premia of certain banks shows that ECB diagnostics in the Thematic Review on Climate were accurate in identifying the banks that need stronger supervisory focus.

JEL codes: G12, G21, Q51, Q54, R32

Keywords: Climate Change, Residential Real Estate, Asset Pricing, Residential Mortgage Backed Securities, Bank Lending Standards

Non-technical summary

Climate risk has the potential to pose systemic risks to financial markets and financial institutions. As climate change accelerates, the frequency and severity of extreme weather events, regulatory shifts and shifts in public sentiment are likely to rise. These factors and uncertainty around them can adversely impact asset valuations, creditworthiness, and overall market dynamics. The interconnected global financial system implies that shocks originating from climate-related events could cascade across sectors and geographies, potentially leading to a domino effect on financial institutions. Failure to correctly recognize these risks may result in abrupt market corrections or impaired credit portfolios.

Real estate is one of the asset classes which is affected by climate change, and given the size of mortgage lending, it is highly relevant for banks and the overall financial system. Physical climate risk is likely to increase potential damages to houses, which in turn should have an impact on house prices, affecting potential losses by banks by increasing the loss given default on mortgage loans. However, the probability of default of households holding mortgages is also likely to increase in line with increased severity of climate events. This may happen as some sectors or employers may be negatively affected by climate change, resulting in reductions in employment and hence increases in default probabilities of affected households.

The growing recognition of environmental challenges had prompted heightened awareness among market participants regarding the profound impact of climate risk on financial markets and institutions. This awareness resulted in increased incorporation of climate considerations into strategies and risk management practices, but also led to increasing coverage of climate risk by publications, for example by the European Central Bank (European Central Bank, 2019, 2020a).

Motivated by the relevance of climate change for financial intermediaries via residential real estate markets, our paper aims at analysing if physical climate risks are being reflected in residential real estate loan rates of banks, i.e. if higher mortgage rates at origination are charged when the property used as collateral is located in areas exposed to higher physical climate risk. Furthermore, we also analyse differences across banks and check if banks assessed by the SSM as adequately taking climate risks into account in their credit risk management charge higher risk premia than other banks.

To analyse these questions, we use loan-level data for mortgages originated between 2010 and 2023 in 8 euro area countries (Belgium, Germany, France, Ireland, Italy, the Netherlands, Portugal and Spain), provided by the European Data Warehouse. We augment this dataset by the physical climate risk score of the area where the purchased property is located, provided by Four Twenty Seven. Finally, we also supplement our data with the results of a Targeted Review of Climate and Environmental Risks which allows us to categorise banks on the basis of the supervisory assessment of the extent to which they take climate risk into account in their credit risk management.

We find evidence that residential mortgage rates at origination are influenced by climate risk. There is a significant positive risk premium, which increases over the recent years. However, there is significant heterogeneity in the extent to which climate risk is priced. Significant institutions that the ECB identified as "adequately" considering climate risk in the credit risk management charge higher risk premia which have been increasing particularly after the publication of supervisory expectations. The lack of risk premia for institutions which are "inadequately" considering climate risk shows that ECB diagnostics in the Thematic Review on Climate were accurate in identifying the banks that need stronger supervisory focus.

We conclude with two recommendations. The first recommendation is to urge those banks that do not currently incorporate climate risk into their day-to-day operations to do so. While the true probability and impact of climate events occurring is still ambiguous, the fact that it is increasing is clear. Second, we recommend supervisors to step up efforts to move banks into the right direction.

1 Introduction

Climate risk has the potential to pose systemic risks to financial markets and financial institutions. As climate change accelerates, the frequency and severity of extreme weather events, regulatory shifts and shifts in public sentiment are likely to rise. These factors and uncertainty around them can adversely impact asset valuations, creditworthiness, and overall market dynamics. The interconnected global financial system implies that shocks originating from climate-related events could cascade across sectors and geographies, potentially leading to a domino effect on financial institutions. Failure to correctly recognize these risks may result in abrupt market corrections or impaired credit portfolios.

Real estate is one of the asset classes which is affected by climate change, and given the size of mortgage lending, it is highly relevant for banks and the overall financial system. Physical climate risk is likely to increase potential damages to houses, which in turn should have an impact on house prices, affecting potential losses by banks by increasing the loss given default on mortgage loans.[1] However, the probability of default of households holding mortgages is also likely to increase in line with increased severity of climate events. This may happen as some sectors or employers may be negatively affected by climate change, resulting in reductions in employment and hence increases in default probabilities of affected households.

The growing recognition of environmental challenges had prompted heightened awareness among market participants regarding the profound impact of climate risk on financial markets and institutions. This awareness resulted in increased incorporation of climate considerations into strategies and risk management practices, but also led to increasing coverage of climate risk by publications, for example by the European Central Bank (hereafter ECB). Among the many such publications are the Single Supervisory Mechanism (hereafter SSM) supervisory priorities which first mentioned climate risk as a significant risk driver relevant from 2020 onwards (European Central Bank, 2019). Furthermore, the ECB Banking Supervision also published detailed information about the supervisory expectations on how to take climate risk into account in day-to-day business, which also included risk management practices (European Central Bank, 2020a). Motivated by the relevance of climate change for financial intermediaries via residential real estate markets, our paper aims at analysing if physical climate risks are being

[1] It is noteworthy that there is insurance against physical events affecting houses. However, insurance coverage is far from complete and thus cannot shield banks from losses. Climate insurance data is only available as estimated coverage on country level. We therefore refrain from controlling for this as this is covered by our country fixed effects. See also European Insurance and Occupasional Pension Authority (2023).

reflected in residential real estate loan rates of banks, i.e. if higher mortgage rates are charged when the property used as collateral is located in areas exposed to higher physical climate risk. Furthermore, we also analyse differences across banks and check if banks assessed by the SSM as adequately taking climate risks into account in their credit risk management charge higher risk premia than other banks.

To analyse these questions, we rely mainly on three data sources, the first for residential real estate-related loan-level data, the second for climate risk assessment and the third used to better understand bank heterogeneity. Other data sources are used for controls. The residential real estate-related loans are collected from the European Data Warehouse (hereafter EDW), which provides loan-level data underlying securitisations. As our source of climate-related information, we have chosen Four Twenty Seven (hereafter 427) because it covers a wide range of hazards and provides a high level of granularity. 427 distinguishes six different climate-related perils: floods, heat stress, sea-level rise, water stress, windstorms and wildfires. We also supplement our data collection with confidential data from the SSM. This data is the result of a Targeted Review of Climate and Environmental Risks (hereafter TR) (see European Central Bank, 2022). This data allows us to categorise banks on the basis of the supervisory assessment of the extent to which they take climate risk into account in their credit risk management.

To empirically test whether climate change is a driver of residential mortgage rates, we use pooled cross-sectional regressions at the loan level at origination. With respect to climate data, we use different approaches to measure the risk associated with a given region. In contrast to a large body of the literature, we decided to analyse multiple climate perils at the same time. We believe that it offers value added to the literature to create an aggregate measure of climate risk spanning several climate perils (see also footnote 9), and to check how that aggregate risk is reflected in banks' mortgage rates. This new approach that we propose aims at providing a first attempt at the 'big picture' of the climate risk on banks decisions - as of course the climate risk is only one of many that banks consider when extending loans, and the more disaggregated the climate risk considered is, the more fragmented picture the analysis can provide.

We find evidence that residential mortgage rates are influenced by climate risk. Over the sample period the average bank took climate risks into account as loans secured by real estate in high climate risk areas were more expensive than loans with the same characteristics but in safer regions. However, the effect we find seems to be rather small economically, ranging between 4bps and 37bps per standard deviation increase in climate risk. Based on a simple stylized exercise using strong assumptions, we hypothesize that climate risk, while taken into account in recent years, is still underpriced by the average bank. Yet, it is beyond the scope of this paper to define climate risk premia in a normative manner.

Next, we find that banks had not been considering climate risk in their decision making early in the period we consider, but this seems to have changed in recent years, with the coefficient on the climate risk turning positive and significant since around 2016. This timing coincides with the Paris Agreement, which concluded on 12 December 2015. The Paris Agreement set long-term goals aiming at reducing greenhouse gas emissions, and committed countries to work together to adapt to the impacts of climate change. As the Paris Agreement had been a high profile event with extensive coverage by media, we consider it likely that it could have contributed to an increased awareness of importance of climate risk by banks.

However, there is significant heterogeneity in the extent to which climate risk is priced. SSM significant institutions that the ECB identified as "adequately" considering climate risk in the credit risk management charge higher risk premia which have been increasing recently, particularly after the Paris Agreement and more recently after the publication of supervisory expectations. The lack of risk premia for institutions which are "inadequately" considering climate risk shows that ECB diagnostics in the Thematic Review on Climate were accurate in identifying the banks that need stronger supervisory focus. As the ECB only stepped up efforts and intrusiveness in 2022, the effective impact on banks may possibly be assessed only at some point in the future.

The rest of the paper is organised as follows. Section 2 provides an overview of the existing literature, with section 2.1 summarising research on climate risk's impact on asset pricing in general and section 2.2 reviewing related work that focuses specifically on banks. The data is described in section 3, with a detailed description of the climate risk dataset in section 3.1, the loan-level data from EDW in section 3.2, and of the approach used to merge the two sources in section 3.3. The further data used is described in section 3.4. Section 4 outlines in greater detail the methodology used as well as the hypotheses under investigation, with section 4.1 providing information on the interest rate charged and section 4.2 provides information on the supervisory effectiveness perspective. The results are discussed in section 5, broken down into overarching findings in section 5.1 and their heterogeneity when categorizing banks based on ECB's supervisory assessment in section 5.2. Section 6 discusses the robustness exercises that we run. Section 7 concludes the paper.

2 Literature Review

In section 2.1 we present an overview of existing literature concerning the influence of climate change on the real estate, while section 2.2 discusses research on why related risks are of particular interest for the banking sector.

2.1 Climate risk and real estate

Overall, climate change affects households and hence residential real estate markets through several channels. Some channels include broader economic effects such as reduced productivity due to rising temperatures (Deryugina and Hsiang, 2017; Burke et al., 2015; Carleton and Hsiang, 2016) and negative effects on GDP growth (Colacito et al., 2018). In addition, climate change directly affects households by reducing human capital (Graff Zivin et al., 2018) and changing demographics through factors such as reduced heat-related mortality due to adaptation (Barreca et al., 2016). In addition, climate change has been linked to higher suicide rates (Burke et al., 2018) and increased violent behaviour (Almås et al., 2019). Understanding these different pathways is crucial for a comprehensive assessment of the overall impact of climate change on residential real estate markets. However, the aim of our paper is to better understand the impact of physical climate risk on mortgage loan rates, and so in this section we focus only on the subset of the literature which is relevant for our question. We will now examine the more direct effects that serve as the motivation for our paper.

Much of the asset pricing literature has examined the impact of different beliefs (or perceptions) about risk on asset pricing (see for example Barberis et al., 2001; Bansal and Yaron, 2004; Anderson et al., 2005). As there is still some ambiguity about climate change, e.g. about the frequency and impact of disasters, pricing climate risk is a difficult and uncertain process and can therefore lead to very different outcomes. For example, Bunten and Kahn (2014) provide a theoretical model showing that different beliefs and information lead to underestimation or overestimation of climate risks in low or high risk areas respectively. Baldauf et al. (2020) empirically estimate the price differences due to different beliefs, by asking participants if climate change is happening, and find that properties in believer areas sell at a discount of about 7% per standard deviation of belief compared to denier areas. McNamara and Keeler (2013) use physical and behavioural models to show that differences in beliefs also lead more informed investors to invest more in defensive measures and potentially abandon the property at a later date.

Giglio et al. (2014) show that discount rates for real estate cash flows 100 or more years in the future are around 2.6%. With current average real estate yields closer to 6%, this implies a downward sloping term structure of discount rates. Giglio et al. (2021) build on this approach to show that discount rates for climate risk mitigation need to be carefully considered, as most of the benefits will only be realised in the distant future. In addition, physical climate risk is a form of disaster risk, so investments in mitigation will pay off mainly in the bad states of the world, increasing the value of these investments.[2] Similar to insurance or hedging investments, they should therefore have an expected return below the risk-free rate. Using average, e.g., equity discount rates underestimates the present value of climate risk mitigation investments and would lead to many foregone investments with a positive net present value.

As the risk in residential real estate (RRE) loans should also appear in house price changes, it is worthwhile to look more into this dimension. As we are not only focusing on one hazard, the next paragraphs provide a brief overview of the pricing impact of different hazards.

Hino and Burke (2021) looked at flood plain map data in the US and found that there were no significant price differences for residential real estate in flood plains. They argue that RRE investors are amateurs and often only in the market once, and given the auction-like nature of the market, it only takes one person willing to take the risk without a discount. In contrast, business buyers discount properties located in flood plain maps. Furthermore, they show that flood risk is priced in markets where there are strict disclosure requirements related to flood risk, suggesting that this is likely to be driven by information availability. Gibson and Mullins (2020) examine the price effect following several events related to flood risk in New York. The events examined are i) a new regulation that led to an increase in insurance premiums, ii) Hurricane Sandy, and iii) the updating of flood plain maps. While all these events show price reductions of up to 11%, only a few of them are statistically different (e.g. not affected by Sandy but added to flood plain maps). Beltrán et al. (2018) is a meta-study of papers from 1987-2013 and found a 4.6% discount for flood risk in RRE.

The literature on windstorms is largely focused on the US, given the heavy impact hurricane seasons have on properties. While Below et al. (2017) found a temporary (60 days) -3.8% effect

[2] A simple example is investment in renewable energy. A large body of literature shows a negative correlation between energy prices and economic output, see for example Hamilton (2003). Thus, an investment in renewable energy would pay off in periods of high energy prices and low economic output, or potentially reduce this relationship as energy price fluctuations become more predictable and less driven by global politics. Alternatively, an investment that reduces or even prevents damage from floods will only pay off in times when floods do occur.

of hurricanes on RRE, Ortega and Taspinar (2017) show a -17% to -22% effect on affected properties that partially recovered but remained persistent for a New York City based dataset, as well as a learning effect of properties that decreased in price by roughly 8% even though they were not affected by the event itself. Gete et al. (2024) show that mortgage markets would price hurricane risk with counties most exposed requiring 70% higher implied guarantee-fees than inland counties. Eichholtz et al. (2018) show that commercial real estate (CRE) prices in both hurricane-affected and unaffected but vulnerable areas trade at persistent discounts of 8% (unaffected) to 22% (affected).

For the risk of heat stress, Farzanegan et al. (2020) show that in Iranian regions with more drought there is a negative effect on house and land prices, while in regions that become wetter there is the opposite effect. The effect is economically large, with price decreases of 8% for houses and 12% for land for a unit decrease in a drought index.[3] Hong et al. (2019) investigate the impact of droughts on the profit growth of food companies and show that drought indicators are leading poor stock returns, suggesting that food companies' share prices are underreacting to climate change risk.

To better understand the risk from wildfires, it makes sense to look into the wildland-urban interface - the area where houses are in or near wilderness - which is also increasing. The increase in the wildland-urban interface is also associated with i) more accidentally ignited fires (Syphard et al., 2007; Balch et al., 2017) that ii) are more difficult to fight, iii) are more likely to burn down houses (Calkin et al., 2013; Alexandre et al., 2015) and iv) pose a high risk to people (Radeloff et al., 2005). There are also a number of other risks that are not related to the research at hand (e.g. increased likelihood of disease transmission between species). Radeloff et al. (2018) study the US wildland-urban interface and show that the wildland-urban interface has increased by 33-41%, with 97% of this increase due to new housing. For Europe, there is also evidence of an increase in the size of the wildland-urban interface and associated fire frequency and intensity (Europe (Modugno et al., 2016; Bar-Massada et al., 2023), Southern Europe (Ganteaume et al., 2021), France (Long-Fournel et al., 2013)).

[3] A Standardised Precipitation-Evapotranspiration Index is used to measure droughts. It is a standardised z-score and more negative values indicate stronger droughts. A unit decrease is therefore a one standard deviation decrease in the measure.

2.2 Climate risk and banks

A comprehensive literature review on the effect of climate change risks on banks is provided by de Bandt et al. (2023) and we would refer the reader to there. We will however summarise the publications that are most relevant for our paper here.

According to the TR (see European Central Bank, 2022), depending on the time horizon, $70 - 80\%$ of the 107 significant euro area institutions conclude that climate risks will have a material impact on their risk profile and risk management. These institutions should therefore integrate climate risk into their decision-making (e.g. whether to offer a requested loan) and pricing (e.g. the interest rate offered for a given loan). However, the report also finds that only 10% of institutions use sufficiently forward-looking and granular information to assess and manage their climate risks. As the dataset analysed in this paper (see section 3.2) is geographically focused on the euro area, we will investigate the intersection of banks being active in RMBS securitisations and those that are already taking climate risk into account to see if this has an impact on residential mortgage rates in sections 4.2 and 5.2. Similarly, Krueger et al. (2018) conducted an extensive survey and showed that global real estate investors are also increasingly concerned about climate risks (related to US real estate activities), with many of them focusing on risk management and engagement rather than avoidance. Furthermore, the potential impact of climate risk on the prices of their portfolios is also among the most commonly responded motives, which are i) reputational, ii) moral and legal, iii) portfolio risk and return based.

Lazarus et al. (2018) show that houses destroyed by hurricanes are often rebuilt and in many cases even enlarged, thus increasing exposure rather than reducing it. In some countries (e.g. Germany), rebuilding at the same place is even part of the requirements for an insurance company to pay for the damages, thus also not reducing the risk to properties. Ouazad and Kahn (2021) show that after natural disasters, lenders are more likely to approve mortgages that can later be securitised (i.e. sold to Fennie Mae and Freddie Mac) and are therefore less concerned about climate risk. This effect is also more pronounced after events that raise awareness of climate risk without directly affecting the areas. Similarly, Keenan and Bradt (2020) show that mortgage lenders are more likely to securitise loans from areas at high risk of sea level rise.

As banks can be considered as investors in large portfolios of RRE transactions - in this paper focusing on those they have sold to other parties - it is also useful to consider the view of the leading rating agencies on this issue. In principle the credit risk of a security should be properly reflected by the rating they have received from the credit rating agencies. However, as the global financial crisis has shown, that this is not always the case, leading investors to price further risks on top of the credit ratings when making their investment decisions (Fabozzi et al., 2022; Vink et al., 2021). Fortunately, all of the leading rating agencies publish their rating methodologies for RMBS. None of the disclosed RMBS rating criteria mentions climate, and by extension climate risk (Moody's Investor Service, 2023; S&P Global Ratings, 2023; Fitch Ratings, 2023; Morningstar DBRS, 2023). S&P Global Ratings (2021) also provides a FAQ where they argue that physical climate risk could make lenders reluctant to lend and that materialisation would lead to lower recovery values in the event of default. However, they conclude that RMBS pools are geographically diversified and therefore have low exposure to physical climate risk.

3 Data

The analysis presented is based on a combination of different sources. For climate hazard data, we use 427, as it provides detailed information on various climate hazards at a high geographical resolution. To understand bank lending, we use at-origination loan-level data from RMBS from the EDW. We supplement the data with information from a number of additional data sources. Data from Eurostat is used to better reflect regional differences, e.g. a mapping that allows the highly granular climate dataset to be combined with more coarse loan-level data. In addition, some statistical, macro and bank-specific variables are used as controls in our analysis.

3.1 Physical climate risk data

To gain a better understanding of climate hazards, the 427 dataset was used. The dataset provides climate risk indicators for different hazard categories, namely floods, heat stress, hurricanes & typhoons, sea-level rise, water stress and wildfires, each of which is composed of different sub-categories.[4] These different climate risk indicators are generated from sub-indicators.[5]

The relevant risk indicators are linked to a specific location and are therefore available at a sufficiently high resolution to be able to locate them on a map (i.e. country, city, postcode, street and house number are usually available). A limitation of the dataset is that the data points are not evenly distributed, i.e. the resolution is not based on a grid or similar, but rather on the existing physical locations of the company's facilities. However, for our analyses we have to rely on coarser measures of location (e.g. NUTS3 code[6] or potentially truncated postcodes), which largely eliminate the risk of a location having no climate risk indicators, but potentially bias the aggregation towards more commercial areas. It is therefore necessary to combine several different indicators within a region into one statistic for the whole region.[7] All indicators in a region are aggregated using simple statistical averages.

Unfortunately, there are no time series of 427 climate data that would allow us tracking the climate risk over time. In our analysis we use the 2020 vintage of the data. This may create an information mismatch, as the physical climate risk assessment may have been updated and therefore differ from the assessment from the time a loan was issued.[8]

In analysing the relationship between physical climate risk and mortgage rates, we use a measure of climate risk aggregating various hazard-specific climate measures. Our decision is in

[4]For flood risk, the elements used to calculate the overall flood risk score are: flood frequency, flood severity, rainfall intensity, very wet days ($> 95^{th}$ percentile) and wet days ($> 10mm$). For heat stress risk, the sub-indicators are extreme temperatures, extreme heat days and energy demand. For the risk of sea level rise, the absolute and relative frequency of coastal flooding are considered. For water stress risk, the inputs to the overall water stress indicator are current baseline water stress, current inter-annual variability, future water demand, future water supply, change in water demand and change in water supply. For wildfire risk, high wildfire potential days, change in high wildfire potential days, maximum wildfire potential and change in maximum wildfire potential are considered. For windstorm risk, only cumulative wind speed is considered.

[5]As this is not a climate science paper aimed at better understanding the components of these hazards, we take the aggregation approaches as given.

[6]Regulation (EC) No 1059/2003 of the European Parliament and of the Council of 26 May 2003 on the establishment of a common classification of territorial units for statistics (NUTS). It is worth pointing out that the geographical resolution varies by country. The correspondence of NUTS3 in BE is on "Arrondiseements", in FR on "Departments", in DE on "Districts", in IE on "Regional Authority Regions", in IT on "Provinces" or "Metropolitan Cities", in NL on "COROP regions", in PT it's groups of municipalities and in ES it's mostly "Provinces" or individual Islands.

Although the size of NUTS3 regions varies considerably, we have also included the area within each NUTS3 region, as well as the size of the working age population as control variables, and found that our results are robust to their inclusion.

[7]Even if the full postcode was available in the EDW, some aggregation is necessary as in most European countries there are several properties in the same postcode region.

[8]The number of climate events we will experience in the future will largely depend on our net emissions and whether we reach tipping points in the future. The Intergovernmental Panel on Climate Change (IPCC, 2023) has created scenarios with its Representative Climate Pathways, which are loosely based on the additional energy influx by 2100. Given that much of the emissions are likely still to come and the tipping points are still to be reached, ambiguity about the price of climate change is also likely to persist for several decades.

contrast to a large body of the literature, which tends to focus on one climate peril at a time. Of course, such focused analyses have the benefit of providing more detailed insights into the effect of a given climate risk for the residential real estate markets. In particular, we fully acknowledge that different types of climate risk will affect the loss on a given loan differently, i.e. some more via loss given default, some more via probability of default, and hence analyses focusing on one type of peril at a time can analyse their effect on bank lending in more detail. However, we believe that our alternative approach offers value added to the literature as it aims at providing a first attempt at the 'big picture' of the climate risk on banks decisions. Its value stems from the fact that the climate risk is only one of many that banks consider when extending loans, and the more disaggregated the climate risk considered is, the more fragmented picture the analysis can provide.

Regarding our computation of the aggregate climate risk metric, 427 provides a risk score between 0 and 100 for each hazard. Depending on this risk score, each facility covered by 427 is assigned a certain hazard-specific risk level with the categories "low", "medium", "high" and "red flag", using cut-off points specific for a given risk. To obtain a measure that captures the overall climate risk, we transform these risk level categories into a numerical variable that can then be summed over all hazards. For this transformation, "low" is considered the baseline and is assigned a score of 0, "medium" a score of 1, "high" a score of 2 and "red flag" a score of 3. This gives a theoretical range from 0 (no risk at all) to 18 (all risks are red flags). However, the empirical distribution does not have the full range, but reaches a maximum of 11.[9] Descriptive statistics based on the different countries can be found in tables 1 and 9 to 11 or more visually in figs. 5 to 6 for individual risks and fig. 1 for the combined score used in later parts of the paper.[10]

The data is cleaned (e.g. removing postcodes that do not match the official specification of the country), enriched (i.e. adding NUTS3 codes based on existing postcodes) and aggregated

[9]We also used a specification where "high" and "red flag" were assigned a score of 1 and all others zero, effectively reducing the aggregate risk score range to 0-6 - with an empirical maximum of 4. A further approach is using a dummy that is one if and only if at least one hazard is "high". A final approach considered is to normalise the scores to have a mean of zero and a standard deviation of one, and to sum these normalised scores. The results described later in the paper are robust to these different approaches.

[10]It should be noted that the visual representation is based on the NUTS3 level, which is the coarsest geographical categorisation we use - whereas in the dataset we use the highest granularity available. Therefore, this graph does not fully represent the heterogeneity in the data, including the empirical range of observations. There are two reasons for this choice. First, there is no dataset that provides postcode boundaries for all countries of interest. Second, in some countries the resolution of the postal codes is very granular, so that for a given NUTS3 region there are between two (e.g. BE, DE, FR, IE) and five (NL) digit postal codes, which reduces the value of such a visualisation.

to postcode and NUTS3 level to allow easier combination with our other data sources.

Table 1: Country by country breakdown of 427 risk exposures: Average scores

Country	#NUTS3 regions	Earthquakes	Floods	Heat Stress	Sea Level Rise	Windstorms	Water Stress	Wildfire
All	783	37	24	28	5	2	34	40
BE	44	57	24	23	2	0	42	29
DE	400	38	26	25	2	0	26	32
ES	58	16	16	36	15	5	48	62
FR	101	22	25	31	4	4	34	46
IE	8	0	34	5	20	30	25	24
IT	107	62	21	39	12	0	47	53
NL	40	28	29	19	7	6	38	25
PT	25	14	12	38	11	10	47	71

Source: 427 and Eurostat
For all risk areas, the table displays the average score within a given NUTS3 region in the respective country.

3.2 Loan-level data

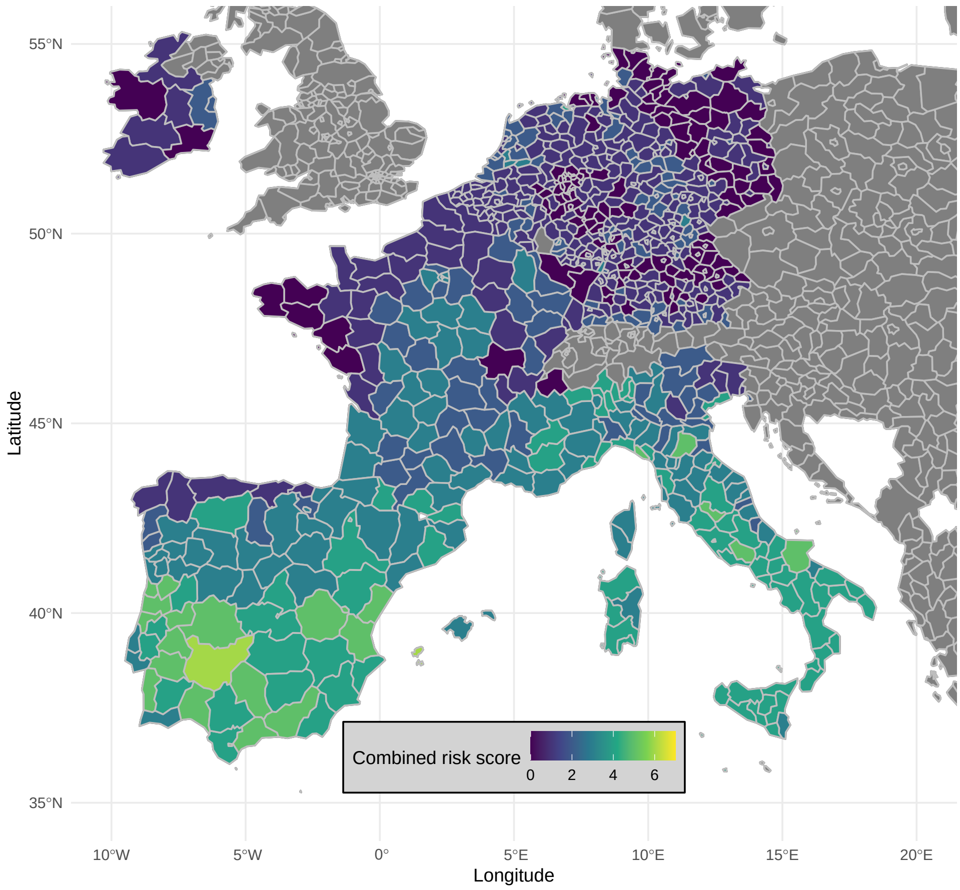
Our paper uses the EDW, a securitisation data repository that contains information on all securitisations eligible as collateral for the ECB liquidity-providing operations. The database has been designated by the European Securities and Markets Authority (ESMA) and the Financial Conduct Authority (FCA).[11]

However, as not all banks are active in the market, EDW covers only 10 countries. As the EDW data is a joint effort between ESMA and the FCA, some British (UK) data is also available but is excluded from our analysis. In addition, Sweden (SE) is also present in the market, but we have seen few securitisations to date and have therefore excluded it from all further analysis. Thus, we cover 8 countries in our analysis. The amount of RMBS transactions covered by EDW and of interest to us covers a total of 9.2 trillion €, spread across 852 securitisations and 83 million unique loans[12]. Overall, the covered market can be divided into three different categories: France (FR) is a country with a moderate number of securitisations, but these securitisations were rather large in terms of loan value, covering around 40% of our sample in terms of loan value, but less than 10% in terms of securitisations. The next category includes Spain (ES), Italy (IT), Netherlands (NL), all of which are quite active in the market and have a large number of securitisations, around 20% of our total each, but are slightly below average in terms of loan value. The final category is of countries that have either fewer securitisations or mostly smaller

[11] For more information on the EDW securitisation repository, see the EDW website.

[12] With the change in reporting templates that occurred in 2020, there is a risk of double counting some loans as the unique identifiers between the old and new templates may be different. However, the number of securitisations using the new templates is rather limited at around 150, of which only $\approx \frac{2}{3}$ of these report both new and old templates.

Figure 1: Combined climate risk score per NUTS3 region.



ones, so Belgium (BE), Germany (DE)[13], Ireland (IE) and Portugal (PT).

While EDW contains a large number of loans, our loan-level analysis focuses on a subset. The database we use contains a cross section of more than 6 million loans to facilitate the purchase of residential properties that were originated between 2010 and 2024. As loans tend to enter an asset-backed security with a lag from the origination date, the volume of loans included in our dataset decreases over time (see fig. 2).[14] Figure 3 shows the approximate[15] share of new loans covered by our dataset per country over time, and confirms the sharp decline for the last few

[13] While DE is the largest economy in Europe, DE banks are not very active in this market as they are frequent issuers of Pfandbriefe: Covered bonds have been around for centuries and are a significant part of the DE and therefore European bond market. Similar to RMBS, they are asset-backed securities but follow a different set of rules and regulations and are therefore not covered by EDW.

[14] The pattern for IT and IE is a bit different, as the share of loans increases around 2018-2021 and falls only afterwards.

[15] We use as the denominator loans to households for house purchase (new business) at country level from MFI Interest Rate Statistics, aggregating monthly series to annual.

Table 2: Descriptives of RMBS data in EDW

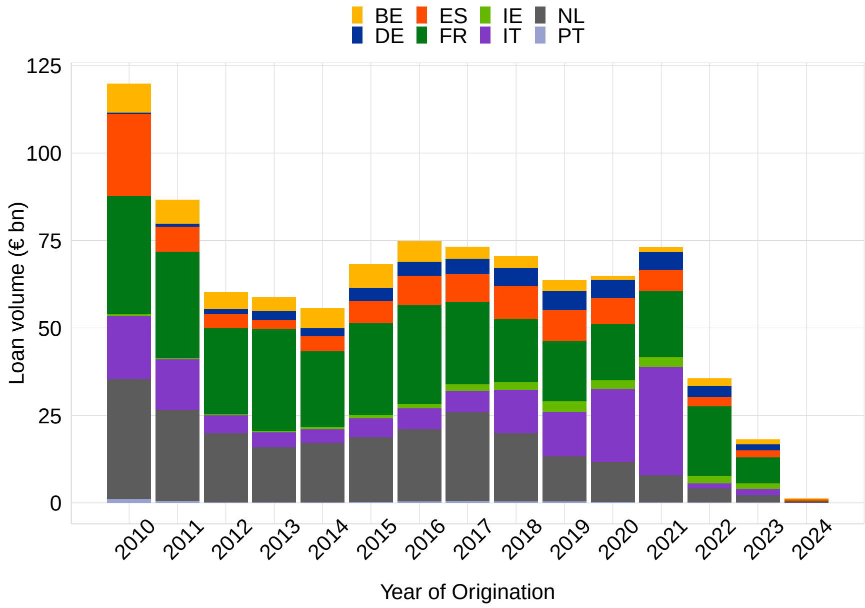
Country	#Securitisations	#Loan-Periods	#unique Loans	Value of loans secured (€)
All	852	659.7M	83.1M	9.2T
BE	22	51.6M	4.4M	287.5B
DE	11	50.7M	2.8M	297.1B
ES	225	77.6M	6.2M	1.5T
FR	55	148.8M	38.7M	3.9T
IE	61	22.9M	1.2M	224.9B
IT	150	66.8M	6.9M	1.2T
NL	218	145.0M	13.2M	1.1T
PT	42	20.9M	2.1M	127.3B

Source: EDW
The securitisations are identified by EDW internal IDs. A set of loan identifiers is used to determine the uniqueness of a given loan.
The value of loans secured is based on the maximum value of the outstanding amount of a given loan.

years in each of the countries covered, with shares falling from as high as around 60% in some countries to close to zero in 2024. The share of total mortgage lending covered by EDW data also varies across countries, ranging from an average of 2% in DE (see footnote 13) to 22% in ES (see fig. 3).

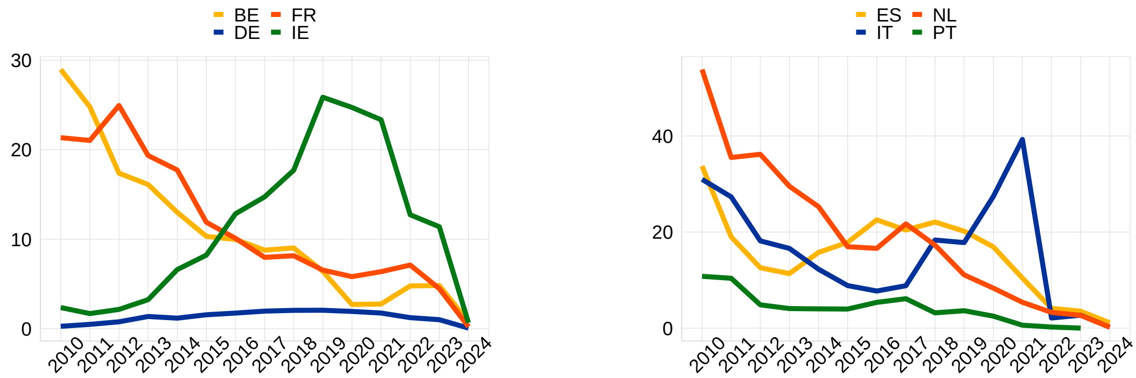
Securitised loans included in EDW data represent only a fraction of banks portfolios, which is a caveat of our analysis. The literature on the credit quality of securitised loans is inconclusive. Some studies show that securitised loans may be of lower quality than loans that remain on banks' balance sheets (see Keys et al. (2010)), while other studies find the opposite. Namely, Albertazzi et al. (2015) and Bonner et al. (2016) find that the main motivation for euro area banks to issue asset-backed securities is funding rather than risk mitigation, and therefore securitised loans should be no riskier than other loans. However, despite the caveat related to the fact that only a fraction of euro area market is covered by our analysis, we still consider the EDW dataset to be very useful for empirical analysis of the kind of ours. First, there is no other mortgage loan-level dataset that would contain loans from several euro area countries. AnaCredit for households does not exist, and country-level credit registers could not be combined into one dataset due to different methodologies and/or definitions of the data. Second, comparison of evolution of EDW-based data with statistics from other sources provides a reassuring picture. For example, an analysis of the default frequencies of the loans considered in this study does not reveal substantial deviations from historical default frequencies on a larger pool of mortgage loans. In addition, also mortgage interest rates registered in EDW follow the trends of official statistics, as described in more detail below. Finally, as the lender takes many factors into account when deciding which loans to securitize, and we look at climate risk premia ar origination, we believe there is no reason to expect a correlation between climate risk (mis)pricing and the fact that a given loan was selected into our sample by being securitized.

Figure 2: Loan volumes per year per country



Source: EDW

Figure 3: Shares of new loans covered per year per country



Source EDW and MIR

Our main variable of interest is the interest rate charged for a given loan in percent (at origination). Table 3 shows the descriptive statistic, and Figure 4 - the behaviour over the relevant years.

Regarding the general evolution of mortgage interest rates at origination included in our dataset, there is a significant decline between 2012 to 2021, and a sharp increase starting in 2022. This evolution in line with the behaviour of the general level of interest rates in the period we analyse.[16]

Summary statistics of the main control variables, i.e. the loan-to-income ratio at origination (OLTI), the loan-to-value ratio at origination (OLTV) and the loan maturity, are shown in table 3. The OLTI is the loan balance at origination as a proportion of the sum of primary and secondary income[17], which is one of relevant variables affecting the probability of default of a loan. The OLTV is the loan balance at origination as a proportion of the purchase value, which can be considered as a proxy for the loss given default of a loan. The loan term variable indicates the number of months as agreed in the original contract and is thus an indicator of the duration of the loan.

In addition, the EDW data includes a wide range of borrower and loan characteristics that could potentially be useful as control variables. However, only 55 out of more than 160 variables are required to be reported, and the reporting of non-mandatory information tends to be low, which limits its usefulness.[18] In addition, some information such as location, which could potentially be used to identify an individual, is pseudonymised in order to protect the privacy of the respective borrowers. In particular, NUTS3 codes are only partially available and postcodes are mostly 'truncated' (i.e. only the first few digits/characters are available) to reduce geographical resolution. Whenever possible, the truncated postcodes are used to fill in missing NUTS3 codes using a postcode to NUTS3 mapping from Eurostat (see section 3.4). In case a truncated postal code is not fully embedded in a NUTS3 code, the most frequent NUTS3 region is taken instead. In the worst case, this could be the neighboring region instead of the correct region, but would likely still have rather comparable physical climate risk.

Finally, several cleaning steps are performed. First, as loans originated in the Netherlands tend to be split into two or more entries in the EDW, we consolidated them into unique loans, assuming that loans to the same borrower in the same country, secured by the same property and originated in the same month are in practice the same product. Furthermore, some outliers are removed from our sample. An outlier is identified if the OLTV is negative or in the top 0.3% of all loans, the loan amount is in the top 0.3% of all loans, the loan term is in the top 1% of all

[16] For the evolution of mortgage interest rates over time see for example ECB's Financial Stability Review November 2023, chart 1.9.

[17] Missing values of secondary income are treated as zero.

[18] This relates, for example, to the age of the borrower, which could be calculated from the optional date of birth.

Table 3: Descriptive statistics of EDW data used in loan-level regressions

Country	Type	Minimum value	25% quantile	Average value	75% quantile	Maximum value	StdDev	Number of values
All	Interest Rate	0.00	1.41	2.29	3.09	9.75	1.21	6,084,990
All	Loan term (m)	0	204	272	360	480	91	6,084,990
All	OLTI	0.24	1.91	3.72	4.93	15.00	2.45	6,084,990
All	OLTV	0.00	0.58	0.76	0.98	3.00	0.30	6,084,990
BE	Interest Rate	0.00	1.99	2.71	3.52	6.83	0.98	445,704
BE	Loan term (m)	2	215	249	300	480	69	445,704
BE	OLTI	0.24	1.23	2.46	3.21	15.00	1.71	445,704
BE	OLTV	0.00	0.50	0.76	1.00	3.00	0.36	445,704
DE	Interest Rate	0.00	1.20	1.87	2.35	9.50	0.91	274,150
DE	Loan term (m)	5	121	231	328	480	114	274,150
DE	OLTI	0.24	2.01	3.80	5.06	15.00	2.40	274,150
DE	OLTV	0.00	0.46	0.72	0.95	3.00	0.35	274,150
ES	Interest Rate	0.00	0.61	1.50	1.99	9.75	1.19	699,422
ES	Loan term (m)	11	301	363	420	480	81	699,422
ES	OLTI	0.24	1.93	3.83	5.36	15.00	2.61	699,422
ES	OLTV	0.00	0.69	0.77	0.82	3.00	0.20	699,422
FR	Interest Rate	0.00	1.49	2.24	3.10	6.20	1.06	2,500,695
FR	Loan term (m)	1	180	222	300	480	71	2,500,695
FR	OLTI	0.24	1.45	3.04	4.20	15.00	2.08	2,500,695
FR	OLTV	0.01	0.59	0.78	1.00	3.00	0.30	2,500,695
IE	Interest Rate	0.00	2.75	3.11	3.32	7.90	0.72	84,067
IE	Loan term (m)	0	300	334	396	480	76	84,067
IE	OLTI	0.24	2.54	3.04	3.50	14.58	0.88	84,067
IE	OLTV	0.01	0.69	0.76	0.90	2.28	0.17	84,067
IT	Interest Rate	0.00	1.30	2.07	2.40	9.52	1.09	1,166,613
IT	Loan term (m)	0	241	286	361	480	79	1,166,613
IT	OLTI	0.24	3.16	4.89	6.23	15.00	2.34	1,166,613
IT	OLTV	0.00	0.53	0.71	0.80	3.00	0.30	1,166,613
NL	Interest Rate	0.00	2.25	3.26	4.40	9.47	1.24	881,323
NL	Loan term (m)	0	328	336	360	480	49	881,323
NL	OLTI	0.24	2.93	4.65	5.29	15.00	2.86	881,323
NL	OLTV	0.00	0.60	0.80	1.01	3.00	0.29	881,323
PT	Interest Rate	0.00	0.89	1.45	1.89	8.50	0.96	33,016
PT	Loan term (m)	0	360	390	480	480	93	33,016
PT	OLTI	0.24	2.72	4.41	5.71	14.99	2.40	33,016
PT	OLTV	0.02	0.63	0.73	0.85	2.99	0.20	33,016

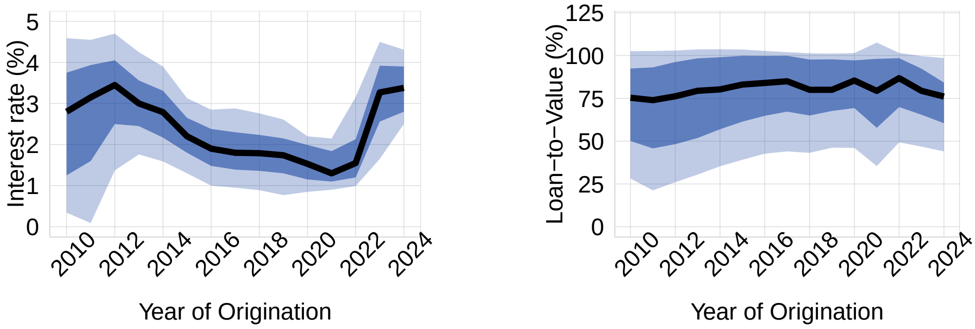
Source: EDW.
All values are at origination. The OLTV and OLTI refer to the Loan-to-Value and Loan-to-Income ratio respectively. The Loan term (m) is the initial time to maturity in months.

loans, or the OLTI is in the bottom 1% of all loans or exceeding 15. We also removed negative interest rates and interest rates above 100%. Finally, the remaining duplicates, identified by identical borrower, loan and property IDs, were removed from the dataset. All descriptive statistics shown are based on the cleaned dataset.

Figure 4: Interest rates and Loan to values over time

(a) Interest rates

(b) Loan to values



Note: Black line show the median. Darker shade show the 25-75th percentile range. Lighter shade show the 10-90th percentile range.

Table 4: RMBS Geolocation data availability in EDW

Country	Both available (%)	Neither (%)	Only NUTS3 (%)	Only postal code (%)
BE	76.7	0.0	1.5	21.8
DE	17.3	0.2	38.0	44.4
ES	84.2	0.8	10.0	5.0
FR	79.3	3.8	14.3	2.6
IE	32.7	0.1	49.2	18.0
IT	90.4	0.7	4.1	4.8
NL	82.8	0.1	9.4	7.7
PT	56.5	0.6	9.4	33.4

Source: EDW
Raw availability of EDW geolocation information. For most analysis, NUTS3 are filled based on zip codes if possible (i.e. for macroeconomic variables that are only available on NUTS3). The values are relative shares of all loans in EDW within the respective country.

Despite the fact that the zip code is a mandatory reporting item in EDW, the availability is somewhat heterogeneous, as can be seen in table 4. However, for the majority of data at least some geolocation info is available, i.e. either the zip code or the NUTS3 classification.

3.3 Joining EDW with 427

As the EDW data contain a lot of information (e.g. year of birth, loan start date, house price, geo-location, property type and many more) that could potentially be used to uniquely identify a

Table 5: Descriptive statistics of our aggregated climate risk measure

Country	Minimum value	25% quantile	Average value	75% quantile	Maximum value	StdDev	Number of values
All	0.00	1.00	2.26	3.00	11.00	1.31	6,084,990
BE	1.00	1.00	1.13	1.00	4.00	0.37	445,704
DE	0.00	0.00	0.72	1.00	3.00	0.67	274,150
ES	0.00	3.00	3.78	4.00	10.00	1.03	699,422
FR	0.00	1.00	1.95	3.00	11.00	1.11	2,500,695
IE	0.00	1.00	1.80	2.00	5.00	1.08	84,067
IT	1.00	3.00	3.28	4.00	8.00	0.93	1,166,613
NL	0.00	1.00	1.61	2.00	8.00	0.79	881,323
PT	0.00	3.00	3.44	4.00	6.00	0.78	33,016

Source: EDW, 427 and Eurostat.
For a given loan in EDW the closest regional identifiers are taken to match the average climate risk scores from 427 (see section 3.3). These average scores are then mapped to the respective risk categories and summed up to arrive at our aggregated climate risk score (see section 3.1).

borrower by name, the data is provided pseudonymised by reducing information on geographical location of the property used as collateral for a mortgage. This complicates somewhat joining of the EDW with the 427. To explain clearly the approach to combining the data, it might be worthwhile illustrating it with a few cases. The easiest case is when the resolution of climate and EDW matches, e.g. they are both available at postal code level, which are then joined. In case the EDW postal codes are truncated (i.e. only the first three digits are shared), we take the climate data from all regions that share the same starting digits and equally weight all observations in those regions. Lastly, in case we have EDW data available but no 427 data, we drop the trailing characters from EDW postal codes until we can match them as discussed in the previous case. Note also that if the postcode is not provided at all, the NUTS3 code is used to obtain the climate risk indicators (see table 4).

3.4 Eurostat and ECB data

In addition to the EDW and 427 data, we also use auxiliary variables from Eurostat and the ECB.

As the data in EDW have different fields for regional identifiers, i.e. postal codes and NUTS3 codes, Eurostat data are used to map postal codes from 427 to NUTS3 regions from EDW. Further Eurostat data are used to align previous NUTS taxonomies with the current NUTS taxonomy.[19] In total, there were 500 such changes between the different versions, of

[19] There are different versions of the legal texts that accompany changes in the taxonomy. If regions are merged, the old NUTS3 codes are recoded to the new NUTS3 codes, e.g. between the 2006 and 2010 taxonomies a new region "Städteregion Aachen" (DEA2D) was created from the old "Kreisfreie Stadt Aachen" (DEA21) and "Kreis Aachen" (DEA25), so both regions were recoded to DEA2D. Where regions are split, the old NUTS3 code is mapped to the new NUTS3 code that is closest in name to the new region, e.g. between the 2006 and 2010 versions, "Milano" (ITC45) was split into "Milano" (ITC4C) and "Monza e della Brianza" (ITC4D), so the old ITC45 was recoded to ITC4C.

which 271 affected countries covered by EDW (see table 1).

Table 6: Descriptive statistics of household cost of borrowing for house purchases

Country	Minimum value	25% quantile	Average value	75% quantile	Maximum value	StdDev	Number of values
All	1.32	1.82	2.55	3.41	4.03	0.89	174
BE	1.43	1.89	2.66	3.48	3.99	0.86	174
DE	1.16	1.76	2.47	3.46	4.22	0.97	174
ES	1.38	1.89	2.47	3.02	3.99	0.74	174
FR	1.10	1.50	2.39	3.42	4.03	1.00	174
IE	2.70	2.94	3.23	3.41	4.23	0.37	174
IT	1.25	1.87	2.67	3.54	4.61	0.97	174
NL	1.65	2.40	3.09	3.93	4.85	0.96	174
PT	0.75	1.40	2.42	3.30	4.65	1.16	174

Source: ECB MFI Interest Rate Statistics.
The data is at monthly frequency and is derived from submissions of monetary financial institutions to the respect competent authority, where it is then aggregated. 'All' refers to a volume weighted average of the eight countries under consideration and is only shown for reference purposes.

In addition, we also use the aggregate level of the cost of borrowing for house purchase for households reported by the ECB as one of our control variables. We use this as a benchmark to cover for country and time heterogeneity as the data is available per country and reported at monthly frequency. It is derived from the population of loans made and thus doesn't suffer from any sample selection bias.[20] Descriptive statistics can be seen in table 6.

4 Methodology

The aim of this paper is to analyse whether physical climate risks are being reflected in residential real estate loan rates of banks. In section 4.1 we explain what methodology we apply to investigate if banks charge a risk premium for higher physical risks for mortgages collateralised by property exposed to physical climate risk. Next, in section 4.2 we show how we analyse if there are significant differences across banks and check if banks assessed by the SSM as adequately taking climate risks in the credit risk management charge higher risk premia than other banks.

4.1 Climate-related risk premia of banks providing residential real estate loans

In this section, we explain how we investigate whether banks charge a risk premium for higher physical risks for mortgages collateralised by property exposed to physical climate risk. When

[20] The rate is calculated on the basis of reports that all euro area monetary financial institutions have to submit to their respective national central banks, which processes the information and reports it to the ECB. The ECB publishes a time series of these benchmark rates in the MFI Interest Rate Statistics

considering whether or not banks should consider climate risk, it is worth starting with a brief thought experiment. Imagine a world where the only risk borrowers face is climate risk. To simplify, let's assume a binomial distribution: regions affected by climate change and regions unaffected. There are two banks in operation, Bank A and Bank B. They differ only in how they manage climate risk in their portfolios. Bank A can distinguish between affected and unaffected regions. It charges risk-free mortgage rates in unaffected regions and a risk premium in affected regions. Bank B, on the other hand, cannot differentiate between the regions. It charges the same mortgage rate in both regions. Initially, Bank B's mortgage rates are equal to Bank A's in unaffected areas and lower in affected areas. In a winner-takes-all environment, Bank B attracts all borrowers from the affected regions, leaving Bank A with no borrowers from these areas. As climate risk materialises, Bank B has to start charging a risk premium on their loans to cover losses. At this point, Bank B can no longer attract borrowers from unaffected regions because Bank A's mortgages are cheaper. Bank B then only lends to borrowers from affected regions, while Bank A lends to those from unaffected regions. Because bank B still cannot differentiate between affected and unaffected regions, Bank B charges the same risk premium on all their loans, equal to the risk premium that Bank A charges for loans in affected regions. Ultimately, Bank A dominates the market in unaffected regions because it can differentiate between the regions. It also competes with Bank B in affected regions, as both banks charge the same premium in these areas. It follows from this thought experiment that banks should charge a risk premium on climate risk. While loan quantities by banks should also be affected by the same mechanism, unfortunately our data, covering only a fraction of the market (see also section 3), would not allow us to analyse this aspect.

We thus test two hypotheses:

Hypothesis 1 *Banks do not charge a risk premium for higher physical risks for mortgages collateralised by property exposed to physical climate risk.*

If climate risk were priced into residential mortgages, we would expect to see a positive premium, indicating that higher climate risk is associated with higher risk for the lender and thus higher mortgage rates for the borrower. This would also be consistent with Do et al. (2020); Javadi and Masum (2021); Nguyen et al. (2022); Barbaglia et al. (2023), who show a positive relationship between some hazards and interest rates for borrowers.

Hypothesis 2 *The extent to which banks take physical climate risk into account when pricing residential mortgage rates has not changed over time.*

If the pricing impact of climate risk is time-varying, we would expect the effect to increase over time. Beyond the natural sciences, awareness and knowledge of climate risk has increased over the past decade(s). Furthermore, the materialisation of risks has also accelerated in recent years, leading to our alternative hypothesis of an increasing coefficient over time.

We employ pooled cross-sectional regressions to test these hypotheses as shown in eqs. (1) and (2) to test hypotheses 1 and 2 respectively:

$$Interest_{i,r,t,c} = \alpha_c + \alpha_t + \beta_1 \times Risk_r + \Gamma \times X_{i,r,t,c} + \varepsilon \tag{1}$$

$$Interest_{i,r,t,c} = \alpha_c + \alpha_t + \beta_2 \times Risk_r + \beta_3 \times Time \times Risk_r + \Gamma \times X_{i,r,t,c} + \varepsilon \tag{2}$$

The left-hand side variable $Interest_{i,r,t,c}$ refers to the interest rate on a residential real estate mortgage i, where the collateral is located in region r and the loan was originated at time t in country c. We use the entire interest rate charged at origination as opposed to focusing for example of the spread, as the latter would be relevant for floating rate loans only, and our approach can be applied to both fixed and floating interest rates loans. The $Risk_r$ is the aggregated physical climate risks in a region r (see section 3.1) and $Time$ are dummies for different periods in the sample.[21] We use fixed effects to capture heterogeneity in the time and country dimensions with α_t and α_c respectively. Depending on the specification, we use a set of control variables $X_{i,r,t,c}$ that are known to be determinants of mortgage rates. The control variables include the employment status[22], the term of the loan, the loan-to-value ratio, the loan-to-income ratio and the benchmark rate for the cost of borrowing for household house purchase in the same country-year-month (see section 3.4). All variables are at origination of the loan except for the physical climate risk indicator which is time-invariant (see section 3.1).

Thus, to empirically test hypothesis 1, we can test whether $H_0 : \beta_1 = 0$ and reject the hypothesis if this is not the case. To test hypothesis 2, we would have to test whether H_0 :

[21] We consider the period from 2010-2012 as our baseline and have dummies for 2013-2015, 2016-2020 and the period after 2021.

[22] The dataset allows to distinguish between the following categories: Employed in the private sector, employed in the public sector, employed in an unknown sector, counterparty is a legal entity, pensioner, self-employed, student, unemployed and other.

$\beta_2 + \beta_3 = 0$ and reject the hypothesis if the joint test is significantly different from zero for at least the most recent periods.

4.2 Differences of climate-related risk premia between banks assessed by supervisors as taking climate risk into account appropriately, and other banks

Over the past few years, ECB Banking Supervision has been raising expectations on banks' integration of climate change into their day-to-day operations. In 2019 the European Central Bank (2020b) conducted a comprehensive analysis of underwriting standards and found only a weak relationship between pricing spreads and the expected loss rate of loans in general. Since then, ECB Banking Supervision published a Guide to banks with supervisory expectations regarding climate risks in November 2020. Following this, the ECB stepped up the gear in tackling climate risks in banks and as part of its supervisory priorities, conducted a TR to gain a better understanding of how significant institutions incorporate climate risks in different areas, including credit risk. The TR started early 2022 and was based on data from 2021. It led to a classification of banks as regards how well they perform in considering climate risk in their operations, and a long list of supervisory findings and mitigation measures communicated to (and to be implemented by) the respective banks. This allows us to get a better understanding of the heterogeneity in banks' practices and of changes thereof over time. If over time supervisory expectations have been implemented by banks, this could contribute to observed improvements in loans pricing practices, i.e. a higher climate-risk premia.

Ideally, we would have liked to assess the effectiveness of SSM's supervisory expectations on bank's decisions on climate risk premia. A standard way to run such an empirical analysis would be to apply a difference-in-differences econometric analysis. However, it would require a control group of banks that have not been subject to SSM's supervisory expectations. Despite our attempts, we had not succeeded at finding one that is also active enough in the market. For example, we considered a group of less-significant euro area institutions, as they are not directly supervised by the SSM. However, those institutions are also aware of the SSM's communication and expectations, and likely to consider them at least to some extent in their decisions, so we did not feel like such a control group would be a correct choice. In the future, when banks have been moved to implement the measures communicated to them as a result of the TR, we would like to take a more holistic view of supervisory effectiveness. Perhaps by then we would be able to identify a viable control group. Furthermore, the SSM also intends to make more use of existing legal instruments, such as periodic penalty payments if banks fail to implement the required supervisory decisions. Once we have the experience of using these instruments, we plan to reassess how we could analyse the effectiveness of supervisory action by the SSM. Alternatively, another idea that we would like to explore in the future refers to comparing climate risk premia between banks and non-banks extending mortgage loans, as non-banks are not subject to climate risk review and rating.

For the time being we are therefore only comparing the outcomes for the group of banks assessed by supervisors as taking climate risk into account appropriately, and other banks. If we find that banks assessed as taking climate risk into account appropriately charge higher climate-related risk premia than other banks, this finding would have many important implications. First, it would increase the credibility of our findings about climate risk-premia. Second, it would support the credibility of the SSM supervisors in assessing the banks' practices with regard to the climate risk. Third, while, as explained above, we cannot claim to analyse causality, we would be likely at least partially capturing the fact that SSM's communication had been effective in impacting banks' practices.

This leads us to a variant of hypothesis 2, namely hypothesis 3

Hypothesis 3 *There are no differences of climate-related risk premia between banks assessed by supervisors as taking climate risk into account appropriately, and other banks.*

We use the originator-specific information from EDW and combine it with supervisory data from the TR.[23] Based on the outcome of the TR, each banking group is assigned to a specific category that summarises how well the group addresses climate risk in the relevant risk area. There are four different categories, namely "inadequate", "somewhat inadequate", "broadly adequate" and "adequate". For our purposes, we identify the set of banking groups that have some "adequate" measures in place when it comes to incorporating climate risk into their credit risk management, i.e. are assessed as "broadly adequate" or "adequate" in the TR. We can now

[23] For matching the datasets, we also use data from the European System of Central Banks Registry of Institutions and Affiliates Data (RIAD), data from the Global Legal Entity Identifier Foundation (GLEIF) and supervisory data to identify the banking group to which a given lender belongs. We use both RIAD and GLEIF to ensure the highest possible number of matches to the respective banking groups, as the two datasets differ in scope and purpose. As a method of last resort, we manually match the email addresses of the contact points to the respective institution.

examine whether these banking groups take climate risk into account when pricing RRE loans. Note that we only consider the set of lenders that can be clearly identified as being part of the banking group of a significant institution, as for all others we have no information on where they stand in terms of considering climate risk in their credit risk management.

$$Interest^{a}_{i,r,t,c} = \alpha_c + \alpha_t + \beta^{a}_{2} \times Risk_r + \beta^{a}_{3} \times Time \times Risk_r + \Gamma \times X^{a}_{i,r,t,c} + \varepsilon \tag{3}$$

In comparison to eq. (2) we split the sample by the outcome of the assessment, as indicated with the a superscript, which can be one of "Adequate", "Somewhat inadequate" or "Inadequate". The rest remains unchanged. Similar to hypothesis 2 and testing hypothesis 3, we can test this empirically using $H_0 : \beta^{a}_{2} + \beta^{a}_{3} = 0$. As alternative hypothesis, we would expect the joint coefficients of recent periods to be positive, significant and significantly increasing, for at least adequate banks.

5 Results

Our regression results confirm in the formal setting that banks are charging a physical climate risk premium when deciding on the mortgage rates. In line with the methodology applied, we have two main findings. First, physical climate risk is priced in by euro area banks, as loans for buildings in areas with higher climate risk carry a higher mortgage rate, all else equal. This risk premium increased over time. Second, a closer look at interbank heterogeneity reveals that this effect is driven by institutions that the SSM has identified as (at least) "broadly adequate" in incorporating climate risk into their credit risk management. This effect has also increased over time. This suggests that the TR assessments are accurately identifying the banks that need a stronger focus to enhance supervisory effectiveness. However, our data is not yet suitable to analyse supervisory effectiveness after the ECB stepped up efforts and intrusiveness in 2022, but as time passes we hope to analyse their effectiveness on banks' decisions.

5.1 Physical climate risk premium in banks' mortgage loan interest rates

The regression results show that lenders take physical climate risk into account when pricing loans in the residential real estate market. Table 7 Model (1) contains the results related to the estimation of the model from eq. (1). From this we derive the following conclusions. The effect

Table 7: Regressions with average climate risk scores for all lenders

	Interest Rate (pct)			
	No controls	Controls	Subperiods	Lender FE
	(1)	(2)	(3)	(4)
Climate risk	0.02^{***} (0.01)	0.02^{***} (0.01)	-0.08^{***} (0.02)	-0.09^{***} (0.02)
Climate risk × Loan issued (2013-2015)			0.11^{***}_{xxx} (0.02)	0.11^{***}_{xx} (0.02)
Climate risk × Loan issued (2016-2020)			0.17^{***}_{xxx} (0.02)	0.16^{***}_{xxx} (0.02)
Climate risk × Loan issued after 2021			0.19^{***}_{xxx} (0.03)	0.19^{***}_{xxx} (0.03)
Controls		✓	✓	✓
Standard-Errors	NUTS2 region			
R^2	0.36626	0.44095	0.44691	0.54728
Observations	6,084,990	6,080,017	6,080,017	5,893,020
Country fixed effects	✓	✓	✓	✓
Year of origination fixed effects	✓	✓	✓	✓
SI or Lender fixed effects				✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

The LHS is the interest rate on a given loan in percentage points. To better interpret the interaction effects, a joint test of the interacted and uninteracted Climate risk coefficients is also performed. The joint test has the H_0: Climate risk+Climate risk$\times B = 0$ and the results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, and year of loan origination fixed effects. Also, to account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions.

of physical climate risk on mortgage rates is positive and significantly different from zero. Over the sample period the average bank took climate risks into account as loans secured by real estate in high climate risk areas were more expensive than loans with the same characteristics but in safer regions, which means we can reject the hypothesis 1.

However, the effect we find is economically small. On average, using a house in an area of average risk as collateral (see table 5) makes borrowing $2.2 \times 2bps = 4.4bps$ more expensive than using collateral in a no risk area. Following Barbaglia et al. (2023), we obtain an idea of how large the premium could be. A rough estimate would be around 40 basis points.[24] Hence, this exercise suggests that climate risk, while taken into account, is still underpriced by the average bank. Yet, it is beyond the scope of this paper to define climate risk premia in a normative manner.

To elaborate on this basic finding, we examine its heterogeneity over time. Table 7 Models (3)-(4) show the results for eq. (2). From there we can conclude that the risk premium has increased over time. The economic effect has also increased, so that households applying for a new mortgage with collateral in a region with average climate risk would have to pay $2.2 \times (19bps - 8bps) \approx 24bps$ more than their counterparts in a region with no climate risk. Similarly, a one standard deviation increase in climate risk would lead to a $1.33 \times (19bps - 8bps) \approx 15bps$ increase in the mortgage rate, which is comparable to a $\frac{1}{8}$ standard deviation increase in the mortgage rate.

Both specifications convey the same message: the positive risk premium charged by banks in table 7 is driven by their activities in the most recent years. We can thus reject hypothesis 2. This suggest that banks had not been considering climate risk in their decisions early in the period we consider. However, this seems to have changed in recent years, which could have been driven either by the increased awareness of the climate risk, or by physical climate risk increasing over time (but as our physical risk scores are fixed in time, we cannot decompose the effect into its drivers).

Table 8: Regressions with average climate risk scores for all Significant Institutions

	Interest Rate (pct)			
	All SIs	Adequate	s Inad	Inad
	(1)	(2)	(3)	(4)
Climate risk	-0.11*** (0.02)	-0.15*** (0.03)	-0.06*** (0.02)	-0.05 (0.04)
Climate risk × Loan issued (2013-2015)	0.12*** (0.02)	0.18*** (0.02)	0.05*** (0.02)	0.07* (0.04)
Climate risk × Loan issued (2016-2020)	0.19^{***}_{xxx} (0.02)	0.23^{***}_{xxx} (0.03)	0.12^{***}_{xxx} (0.03)	0.01_{xxx} (0.04)
Climate risk × Loan issued after 2021	0.22^{***}_{xxx} (0.04)	0.32^{***}_{xxx} (0.05)	0.10^{***}_{xxx} (0.03)	0.02_{xx} (0.04)
Controls	✓	✓	✓	✓
Standard-Errors	NUTS2 region			
R^2	0.55503	0.62173	0.51912	0.53547
Observations	4,605,541	1,602,346	2,872,333	130,862
Country fixed effects	✓	✓	✓	✓
Year of origination fixed effects	✓	✓	✓	✓
SI fixed effects	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

The LHS is the interest rate on a given loan in percentage points. To better interpret the interaction effects, a joint test of the interacted and uninteracted Climate risk coefficients is also performed. The joint test has the H_0: Climate risk+Climate risk$\times B = 0$ and the results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. We split the sample into different subsamples. The 'All SIs' refers to all lenders in the EDW dataset that can be matched to a significant institution supervised by the SSM. 'Adequate' refers to a subset of these institutions that have at least an adequate level of climate risk management (as assessed in the TR). 's Inad' and 'Inad' refer to those in institutions that take climate risk into account somewhat inadequately and inadequately. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Borrower-level credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, and year of loan origination fixed effects. Also, to account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions.

5.2 Differences of climate-related risk premia between banks assessed by supervisors as taking climate risk into account appropriately, and other banks

In this section, we check whether there are differences of climate-related risk premia between banks assessed by supervisors as taking climate risk into account appropriately, and other banks. Similar to the section 5.1, we look at the impact climate risk has on mortgage rates. As we only have information about the extent to which banks take into account climate risk for SSM significant institutions, we restrict the sample to originators that belong to these banking groups.

From table 8 we derive the following conclusions. There are statistically significant differences between the loan pricing of banks belonging to the adequate category and their peers, which are also economically significant. Furthermore, we see that the effect has increased significantly - both statistically and economically - in the period following the publication of supervisory expectations. For the most recent subperiod and banks that are classified as adequately taking climate risk into account, we find a $(32bps - 15bps) * 1.33 = 23bps$ premium per standard deviation increase in climate risk, and a $(32bps - 15bps) * 2.2 = 37bps$ premium when the property is located in average climate risk area compared to no climate risk area.

We can therefore conclude with regard to hypothesis 3, that the SSM has adequately identified banks that take climate change into account in their credit risk management. To establish a causal relationship between supervisory efforts and the extent to which climate risk is taken into account in loan pricing, further analysis needs to be conducted. Yet, the SSM has only recently started to step up the gear when it comes to applying more intrusive measures (e.g. fines) against banks that do not follow supervisory guidance. However, the number of loans in our sample that were issued afterwards i.e. starting in 2023, are currently too few to assess the effectiveness of the supervisory efforts with respect to their impact on pricing. As time goes on, more and more data will become available, allowing us to revisit this hypothesis at a later stage.

Banks that adequately take climate risk into account may be banks with generally better risk profiles and risk management practices. Taking the outcome of the Supervisory Review and Evaluation Process (SREP)[25] conducted by the SSM on an annual basis, we find a positive correlation of the overall SREP assessment score and the SSM's score on whether the banks

[24] See appendix A for details on the calculations of the estimate of the physical climate risk premium.

[25] This process determines where a bank stands in terms of capital and liquidity requirements, as well as the adequacy of its internal arrangements and risk controls.

take climate risk into account appropriately of 0.25. Running the same analysis as shown in table 8 but using the overall SREP score to define subsamples, we find the same picture as with climate risk scores i.e. adequate SREP score banks have the highest and most strongly increasing climate risk premia in mortgage rates. Yet, the estimated premia are smaller than the ones estimated for adequate climate risk score banks. We can infer from this that the SSM efforts on climate risk added value on top of the annual SREP exercise in identifying banks with weak climate risk practices. It is important to increase the scrutiny on banks that are lagging behind, thus making supervision more effective.

6 Robustness

To corroborate our findings that on average banks seem to demand a physical climate risk premium from mortgage borrowers and the premium has increased over recent years, we carry out a set of robustness tests.

We complement the right-hand side variables by the GDP per capita of the respective NUTS3 region for the respective issue year. The results in table 13 are comparable to table 7 and thus the result is not driven by omitting such macro information.

To rule out that the findings are driven by omission of certain bank variables that could change over time, we also employ a selection of bank-specific controls. Those include: the CET1 ratio to proxy for the amount of capital a bank has available, the RoE (after tax) and Net Interest Margin to account for the profitability of the banking group in general and in their lending business as well as the NPL ratio to account for the quality of the loan portfolio. We can see in tables 14 and 15 that this has no significant impact on the findings based on the initial specifications, reported in tables 7 and 8. It is worth noting that the results in table 14 are not the same as in table 7, due to difficulties in mapping the data between supervisory reporting and EDW. Furthermore, as the frequency and availability of banking data might vary, we carry forward and backward our observations to fill in missing values.

Despite rigorous research, in empirical analyses it is impossible to account for all relevant variables, and the omitted variable bias may occur. To assess the impact of omitted variables, we adopt the method outlined in Oster (2017), utilizing the implementation provided by Basu (2022). This method involves conducting regressions with varying control sets and observing changes in the coefficient of interest alongside R^2. In essence, substantial shifts in the coefficient without corresponding changes in R^2 suggest possible bias from omitted variables. The dependent variable in our model is the mortgage rate associated with a specific loan, while the climate risk variable serves as the independent variable of interest.[26] In the baseline regression, we include only year and country fixed effects, excluding other controls such as loan maturity, employment status, loan-to-value and loan-to-income ratios at origination, and the mortgage benchmark. These controls are incorporated in the intermediate regression, which accounts for all observed variables. We postulate a hypothetical full model with an $R^2 = 1$, a conservative assumption. The baseline regression (Model (1) in table 7) yields a climate risk coefficient (standard error) of 0.024(0.009) with an $R^2 \approx 37\%$. This coefficient remains stable at 0.021(0.008) for the intermediate regression (Model (2) in table 7), with an $R^2 \approx 44\%$. The resulting range for the unbiased treatment effect is excluding zero, indicating that our findings are robust to potential omitted variable bias.

We have also separated the different climate risks into separate hazards (table 16 shows which individual hazards are priced). We observe some heterogeneity in how the different hazards are priced, but overall we conclude that this exercise confirms the robustness of our findings. Namely, we find a positive and significant effect of risks related to floods, sea level rise, water stress and windstorms, but the effect is not significant for heat stress and wildfire. While it's possible that these hazards are less relevant for euro area mortgages, it also cannot be excluded that the effect would be visible for some of the countries only, while results in table 16 are based on all 8 countries we have in our sample. However, country-specific and hazard-specific analysis is beyond the scope of our paper, because, as explained in section section 3.1, our ambition is to provide a big picture analysis, and we leave more detailed and disaggregated exercises to other studies.

We also provide an alternative set of regressions including a time-varying physical climate risk. We consider the fact that our metric of climate risk is fixed in time to be a limitation of our analysis, as we expect the actual climate risk to be changing over time. Thus, as a robustness check we created a time-varying climate score, multiplying fixed-in-time 427 metrics by a self-created country-level index of climate risk change over time. For the latter, we used the JRC database of climate events, and employed a negative binomial model to estimate the probability of climate events occurring within a given country over time (see fig. 7 for a visual representation

[26] The method in Oster (2017) is limited to scalar treatment effects, preventing us from including interactions between climate risk and loan issuance periods as done in table 7 specifications (2) and (3) and table 8. Therefore, we adhere to a specification akin to table 7 (1).

of the number of events per country). In case the model[27] gave a significant coefficient for the year, we used the annual growth rate to scale our climate risk exposure accordingly. This approach doesn't change the overall outcome (see table 17, table 18), but only changes the point estimates of the coefficients slightly.

As our climate risk metric is static in time, the introduction of country-year fixed effects absorbs most of the variation we wanted to explore over time. The same is true for our dynamic climate risk indicator, as it is multiplied by a constant per year-country and thus also largely absorbed by the country-year fixed effects. Almost by construction, the dynamic effect disappears in these estimation approaches. However, the overall climate risk premia effect is robust to the inclusion of country-year fixed effects (see table 19 and table 20).

7 Conclusion

The relevance and awareness of climate change has increased in recent years, raising the question of whether climate risk is being considered in residential real estate mortgage loans. In this paper, we looked at several different areas, such as if banks charge a risk premium for mortgages collateralised by property exposed to physical climate risk and if this effect seems to be increasing over time. We also checked if there are significant differences across banks covered by the SSM's supervision, considering the intense work on climate-related risk in recent years.

For the mortgage rates, we see a statistically significant effect of climate risk on the mortgage rate of a given loan. Banks do indeed price in physical climate risk when extending mortgages. The effect has become larger in recent periods, suggesting that this is a more recent development that may continue in the near future as we learn more about the likelihood and impact of climate risk on our lives (see Hino and Burke, 2021; Gibson and Mullins, 2020; Beltrán et al., 2018; Ortega and Taspinar, 2017; Eichholtz et al., 2018; Krueger et al., 2018). However, at this stage, we cannot say which channel (e.g. macroeconomic, human capital, household demographics, or changes in the collateral values etc.) is causal for this difference, only that it is associated with physical climate risk.

There are statistically significant differences between the loan pricing of banks assessed by the SSM as adequate with regard to their treatment of climate risk, and their peers, which are also economically significant. Furthermore, we see that the effect has increased significantly -

[27] We estimate the count of events for a given year solely with a constant and a year coefficient for each country: $Count_c = NegBin(\mu_c, \tau_c)$ with $\log(\mu_c) = \beta_0^c + \beta_1^c Year$

both statistically and economically - in recent years, in particular in the period following the publication of supervisory expectations. We can therefore conclude that the SSM has adequately identified banks that take climate change into account in their credit risk management. It is important to increase the scrutiny on banks that are lagging behind, thus making supervision more effective. It is worth noting that the SSM has only recently started to step up the gear when it comes to applying more intrusive measures (e.g. fines) following the inclusion of climate risk in the supervisory priorities since 2022. Therefore, the number of loans in our sample that were issued afterwards i.e. starting in 2023, are currently too few to assess the effectiveness of the supervisory efforts. With regard to hypothesis 3, we can thus for now only show a correlation between banks that were identified by the ECB at an early stage of the TR to adequately take climate risk into account and charge a climate risk premia in mortgage rates. To establish a causal relationship between supervisory efforts and the extent to which climate risk is taken into account in loan pricing, further analysis needs to be conducted. As time goes on, more and more data will become available, allowing us to revisit this hypothesis at a later stage.

We conclude with two recommendations. The first recommendation is to urge those banks that do not currently incorporate climate risk into their day-to-day operations to do so. While the true probability and impact of climate events occurring is still ambiguous, the fact that it is increasing is clear. Second, we recommend supervisors to step up efforts to move banks into the right direction, such as the ECB has done. ECB diagnostics are already showing an adequate assessment and thereby laying the ground for an effective and targeted strategy for follow up with laggard banks to change their practices.

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9 Annex

A Annex: Risk premium – order of magnitude

We follow Barbaglia et al. (2023) in computing the difference between the spread that should be charged for loans exposed to climate risk, and the spread for other loans, based on:

$$S_{climate} = PD_c * LGD_c - PD_n * LGD_n \tag{4}$$

Where $S_{climate}$ is a risk premium related to climate physical risk. PD_c and LGD_c are PDs and LGDs of loans exposed to physical climate risk, while PD_n and LGD_n are PDs and LGDs of loans not exposed to high levels of physical climate risk. Therefore, in order to compute this risk premium we would need to have information about the PDs and LGDs of climate risk-exposed and non-climate risk-exposed loans, which we do not unfortunately have. However, we can approximate these values and hence the climate risk premium by using some backward looking, stylized assumptions. Therefore, for PD_n and LGD_n we assume the values of 0.9% and 16%, respectively, coming from the European Central Bank (2020b). We are aware that these values refer to all the loans, which would mean that climate risk-exposed loans would be included, but we assume that their share would be low and hence we can treat these values for all loans as our assumption for non-climate risk-exposed loans. In order to obtain PD_c and LGD_c we refer to the literature. Namely, we assume that PD_c would be three times the value of PD_n (odds ratio from Kousky et al. (2020)), and that LGD_c would be based on LGD_n and a discount on property prices located in locations under the risk of flooding of 4.6% from Beltrán et al. (2018).

Based on these stylized, backward looking assumptions, our estimate of the expected physical climate risk premium would be 40 bp. However, we are aware that these calculations have to be treated with caution and interpreted as a rough estimate of a lower bound. First, our baseline for non-climate risk-exposed loans refers in reality to all loans, and as a result we are likely underestimating the risk premium. Second, our assumptions for PDs and LGDs of loans exposed to physical climate risk refer to particular cases (for example Beltrán et al. (2018) focuses on flood risk in the US) and may not reflect perfectly the overall physical climate risk in the euro area. Finally, the numbers we are using are backward-looking, while frequency of climate risk materialisations is increasing over time. In contrast, banks extending mortgages, i.e. long term assets, should be forward-looking in their decisions. However, we still believe that despite caveats, this exercise offers a useful rough benchmark to be able to consider the order of magnitude of the risk premium obtained in our regressions.

B Annex: Supplementary tables and figures

Table 9: Country by country breakdown of 427 risk exposures: Number of observations

Country	#NUTS3 regions	Earthquakes	Floods	Heat Stress	Sea Level Rise	Windstorms	Water Stress	Wildfire
All	783	546	546	560	546	546	559	546
BE	44	837	837	902	837	837	893	837
DE	400	174	174	188	174	174	188	174
ES	58	1026	1026	1028	1026	1026	1028	1026
FR	101	771	772	776	771	771	776	771
IE	8	874	878	941	877	876	895	876
IT	107	811	811	812	811	811	812	811
NL	40	337	337	371	337	337	371	337
PT	25	3053	3054	3054	3053	3053	3054	3054

Source: 427 and Eurostat
For all risk areas, the table displays the average number of observations within a given NUTS3 region in the respective country.

Table 10: Country by country breakdown of 427 risk exposures: Maximum Score

Country	#NUTS3 regions	Earthquakes	Floods	Heat Stress	Sea Level Rise	Windstorms	Water Stress	Wildfire
All	783	100	100	78	94	51	99	94
BE	44	75	96	36	80	26	60	50
DE	400	75	100	50	88	26	78	52
ES	58	84	93	70	87	26	96	94
FR	101	75	98	78	88	51	91	87
IE	8	0	100	10	88	35	76	29
IT	107	100	98	69	94	0	99	87
NL	40	75	96	35	88	27	81	40
PT	25	99	92	60	88	40	66	94

Source: 427 and Eurostat
The table displays the highest respective risk indicator across all NUTS3 regions in the respective country.

Table 11: Country by country breakdown of 427 risk exposures: Minimum Score

Country	#NUTS3 regions	Earthquakes	Floods	Heat Stress	Sea Level Rise	Windstorms	Water Stress	Wildfire
All	783	0	0	0	0	0	0	0
BE	44	46	9	15	0	0	0	22
DE	400	0	5	4	0	0	0	21
ES	58	0	0	13	0	0	14	0
FR	101	0	3	13	0	0	12	21
IE	8	0	14	0	0	27	8	22
IT	107	0	0	28	0	0	11	21
NL	40	0	10	7	0	0	0	21
PT	25	0	2	21	0	0	23	0

Source: 427 and Eurostat
The table displays the lowest respective risk indicator across all NUTS3 regions in the respective country.

Table 12: Regressions with average climate risk scores taking into account the credit risk adequacy assessment

	Interest Rate (pct) All SIs (1)	Interest Rate (pct) All SIs (2)
Climate risk	0.01 (0.01)	-0.07*** (0.02)
Climate risk × Credit risk adequately considered	0.03$_{xx}$ (0.02)	-0.13$^{***}_{xxx}$ (0.04)
Climate risk × Loan issued (2013-2015)		0.05*** (0.02)
Climate risk × Loan issued (2016-2020)		0.13$^{***}_{xxx}$ (0.03)
Climate risk × Loan issued after 2021		0.09$^{***}_{xxx}$ (0.03)
Climate risk × Credit risk adequately considered × Loan issued (2013-2015)		0.19$^{***}_{xxx}$ (0.03)
Climate risk × Credit risk adequately considered × Loan issued (2016-2020)		0.21$^{***}_{xxx}$ (0.05)
Climate risk × Credit risk adequately considered × Loan issued after 2021		0.35$^{***}_{xxx}$ (0.06)
Credit risk adequately considered	-0.13*** (0.03)	0.16* (0.09)
Credit risk adequately considered × Loan issued (2013-2015)		-0.31*** (0.05)
Credit risk adequately considered × Loan issued (2016-2020)		-0.47*** (0.14)
Credit risk adequately considered × Loan issued after 2021		-0.42*** (0.15)
Controls	✓	✓
Standard-Errors	NUTS2 region	
R^2	0.50240	0.51794
Observations	4,605,541	4,605,541
Country fixed effects	✓	✓
Year of origination fixed effects	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

The LHS is the interest rate on a given loan in percentage points. The Credit risk adequately considered dummy is based on ECB internal documents assessing whether a given bank takes climate risk into account in their credit risk decision making processes. It is one if and only if the bank is taking climate risk into account in their credit risk management in an at least "broadly adequate" way. To better interpret the interaction effects, a joint test of the interacted and uninteracted Climate risk coefficients is also performed. In those cases where multiple effects are interacted, e.g. Climate risk$\times B \times C$, the joint test has the H_0 : Climate risk+Climate risk$\times B$+Climate risk$\times C$+Climate risk$\times B \times C = 0$. The results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, year of loan origination fixed effects, and lender heterogeneity fixed effects. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions. To account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW.

Table 13: Regressions with average climate risk scores for all lenders and macro control variables

	Interest Rate (pct)			
	No controls	Controls	Subperiods	Lender FE
	(1)	(2)	(3)	(4)
Climate risk	0.03** (0.01)	0.02** (0.01)	-0.08*** (0.02)	-0.08*** (0.02)
Climate risk × Loan issued (2013-2015)			0.11^{***}_{xxx} (0.02)	0.11^{***}_{xx} (0.02)
Climate risk × Loan issued (2016-2020)			0.17^{***}_{xxx} (0.02)	0.16^{***}_{xxx} (0.02)
Climate risk × Loan issued after 2021			0.18^{***}_{xxx} (0.03)	0.19^{***}_{xxx} (0.03)
log(GDP per capita)	-0.16*** (0.04)	-0.16*** (0.05)	-0.14*** (0.05)	-0.13*** (0.02)
Controls		✓	✓	✓
Standard-Errors	NUTS2 region			
R^2	0.36779	0.44240	0.44816	0.54821
Observations	6,084,990	6,080,017	6,080,017	5,893,020
Country fixed effects	✓	✓	✓	✓
Year of origination fixed effects	✓	✓	✓	✓
SI or Lender fixed effects				✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

The LHS is the interest rate on a given loan in percentage points. To better interpret the interaction effects, a joint test of the interacted and uninteracted Climate risk coefficients is also performed. The joint test has the H_0: Climate risk+Climate risk$\times B = 0$ and the results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. Furthermore, the GDP per capita is also considered as a control variable and is the GDP per capita within the respective NUTS3 region and year. In case no such data is available, the next coarser NUTS region is considered until data becomes available. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, year of loan origination fixed effects, and lender heterogeneity fixed effects. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions. To account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW.

Table 14: Regressions with average climate risk scores for all lenders and bank control variables

	Interest Rate (pct)			
	Controls	Controls incl bank controls	Lender FE	Lender FE incl bank controls
	(1)	(2)	(3)	(4)
Climate risk	-0.12*** (0.02)	-0.12*** (0.02)	-0.10*** (0.02)	-0.10*** (0.02)
Climate risk × Loan issued (2013-2015)	0.13*** (0.02)	0.13*** (0.02)	0.11*** (0.02)	0.10*** (0.02)
Climate risk × Loan issued (2016-2020)	0.21^{***}_{xxx} (0.02)	0.21^{***}_{xxx} (0.02)	0.17^{***}_{xxx} (0.02)	0.17^{***}_{xxx} (0.02)
Climate risk × Loan issued after 2021	0.23^{***}_{xxx} (0.03)	0.24^{***}_{xxx} (0.03)	0.20^{***}_{xxx} (0.03)	0.21^{***}_{xxx} (0.04)
CET1 Ratio		-0.10 (0.84)		1.40 (0.91)
RoE (after tax)		-0.36 (0.54)		-0.11 (0.24)
Net Interest Margin		-3.04 (2.55)		-1.28 (0.94)
NPL/Total loans		1.40 (0.99)		1.30 (0.97)
Controls	✓	✓	✓	✓
Standard-Errors	NUTS2 region			
R^2	0.50773	0.50858	0.54869	0.54909
Observations	4,680,241	4,680,241	4,680,241	4,680,241
Country fixed effects	✓	✓	✓	✓
Year of origination fixed effects	✓	✓	✓	✓
SI or Lender fixed effects			✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

The LHS is the interest rate on a given loan in percentage points. To better interpret the interaction effects, a joint test of the interacted and uninteracted Climate risk coefficients is also performed. The joint test has the H_0: Climate risk+Climate risk$\times B = 0$ and the results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. We also consider some bank performance and risk characteristics to cover for potential heterogeneity with respect to those. They are intended to rule out potential effects from banks that are e.g. in bad financial standing. The CET1 Ratio is the amount of CET1 capital as share of Risk-Weighted-Assets and can be considered as a proxy for the amount of capital available. The RoE (after tax) is the annualised profit and loss (after tax) over equity and can be considered a proxy for the overall profitability of a bank. The Net Interest Margin is interest income minus interest expenses over the financial assets subject to impairments and can be considered a proxy for profitability in their lending operations. The NPL/Total loans which is the exposure towards non-performing over total loans and can be considered as a proxy for the quality of the portfolio. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, year of loan origination fixed effects, and lender heterogeneity fixed effects. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions. To account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW.

Table 15: Regressions with average climate risk scores for all Significant Institutions and bank control variables

	Interest Rate (pct)			
	All SIs	Adequate	s Inad	Inad
	(1)	(2)	(3)	(4)
Climate risk	-0.11*** (0.02)	-0.15*** (0.03)	-0.05*** (0.02)	-0.05 (0.04)
Climate risk × Loan issued (2013-2015)	0.12*** (0.02)	0.18^{***}_{x} (0.02)	0.05** (0.02)	0.07* (0.04)
Climate risk × Loan issued (2016-2020)	0.19^{***}_{xxx} (0.02)	0.22^{***}_{xxx} (0.03)	0.11^{***}_{xxx} (0.03)	0.02_{xxx} (0.04)
Climate risk × Loan issued after 2021	0.22^{***}_{xxx} (0.04)	0.31^{***}_{xxx} (0.05)	0.07^{***}_{x} (0.03)	0.02_{xx} (0.04)
CET1 Ratio	1.68* (0.90)	-2.05*** (0.71)	9.59*** (1.65)	-2.57*** (0.40)
RoE (after tax)	-0.13 (0.24)	-0.09 (0.25)	0.99* (0.50)	1.43*** (0.18)
Net Interest Margin	-1.05 (0.93)	-3.45* (1.91)	-0.25 (0.95)	2.91*** (0.41)
NPL/Total loans	1.26 (0.97)	0.98 (1.13)	-2.53*** (0.71)	-1.60 (4.07)
Controls	✓	✓	✓	✓
Standard-Errors	NUTS2 region			
R^2	0.55547	0.62226	0.52120	0.53607
Observations	4,605,541	1,602,346	2,872,333	130,862
Country fixed effects	✓	✓	✓	✓
Year of origination fixed effects	✓	✓	✓	✓
SI fixed effects	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

The LHS is the interest rate on a given loan in percentage points. To better interpret the interaction effects, a joint test of the interacted and uninteracted Climate risk coefficients is also performed. The joint test has the H_0: Climate risk+Climate risk$\times B = 0$ and the results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. We split the sample into different subsamples. The 'All SIs' refers to all lenders in the EDW dataset that can be matched to a significant institution supervised by the SSM. 'Adequate' refers to a subset of these institutions that have at least an adequate level of climate risk management (as assessed in the TR). 'Inadequate' and 'Inadequate' refer to those in institutions that take climate risk into account somewhat inadequately and inadequately. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. We also consider some bank performance and risk characteristics to cover for potential heterogeneity with respect to those. They are intended to rule out potential effects from banks that are e.g. in bad financial standing. The CET1 Ratio is the amount of CET1 capital as share of Risk-Weighted-Assets and can be considered as a proxy for the amount of capital available. The RoE (after tax) is the annualised profit and loss (after tax) over equity and can be considered a proxy for the overall profitability of a bank. The Net Interest Margin is interest income minus interest expenses over the financial assets subject to impairments and can be considered a proxy for profitability in their lending operations. The NPL/Total loans which is the exposure towards non-performing over total loans and can be considered as a proxy for the quality of the portfolio. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, year of loan origination fixed effects, and lender heterogeneity fixed effects. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions. To account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW.

Figure 5: Risk of earthquakes per NUTS3 region.

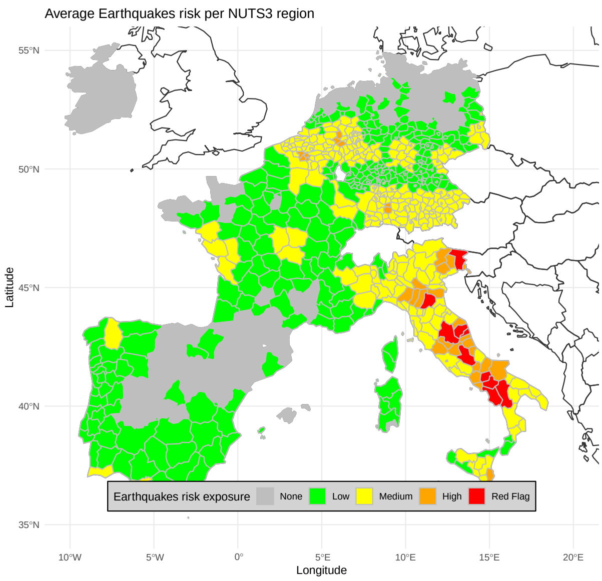

Table 16: Regressions with climate risk category per hazard

	Interest Rate (pct)					
	Flood	Heat Stress	Sea Level Rise	Water Stress	Wildfire	Windstorms
	(1)	(2)	(3)	(4)	(5)	(6)
Hazard Risk score	0.03*** (0.01)	-0.04 (0.03)	0.06*** (0.02)	0.05*** (0.02)	0.03 (0.02)	0.59*** (0.07)
Controls	✓	✓	✓	✓	✓	✓
Standard-Errors	NUTS2 region					
R^2	0.44079	0.44080	0.44072	0.44109	0.44078	0.44067
Observations	6,080,017	6,080,017	6,080,017	6,080,017	6,080,017	6,080,017
Country fixed effects	✓	✓	✓	✓	✓	✓
Year of origination fixed effects	✓	✓	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

To better interpret the interaction effects, a joint test of the interacted and uninteracted Hazard Risk score coefficients is also performed. The joint test has the H_0: Hazard Risk score+Hazard Risk score$\times B = 0$ and the results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, year of loan origination fixed effects, and lender heterogeneity fixed effects. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions. To account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW.

Figure 6: Risk of various physical climate risks per NUTS3 region.

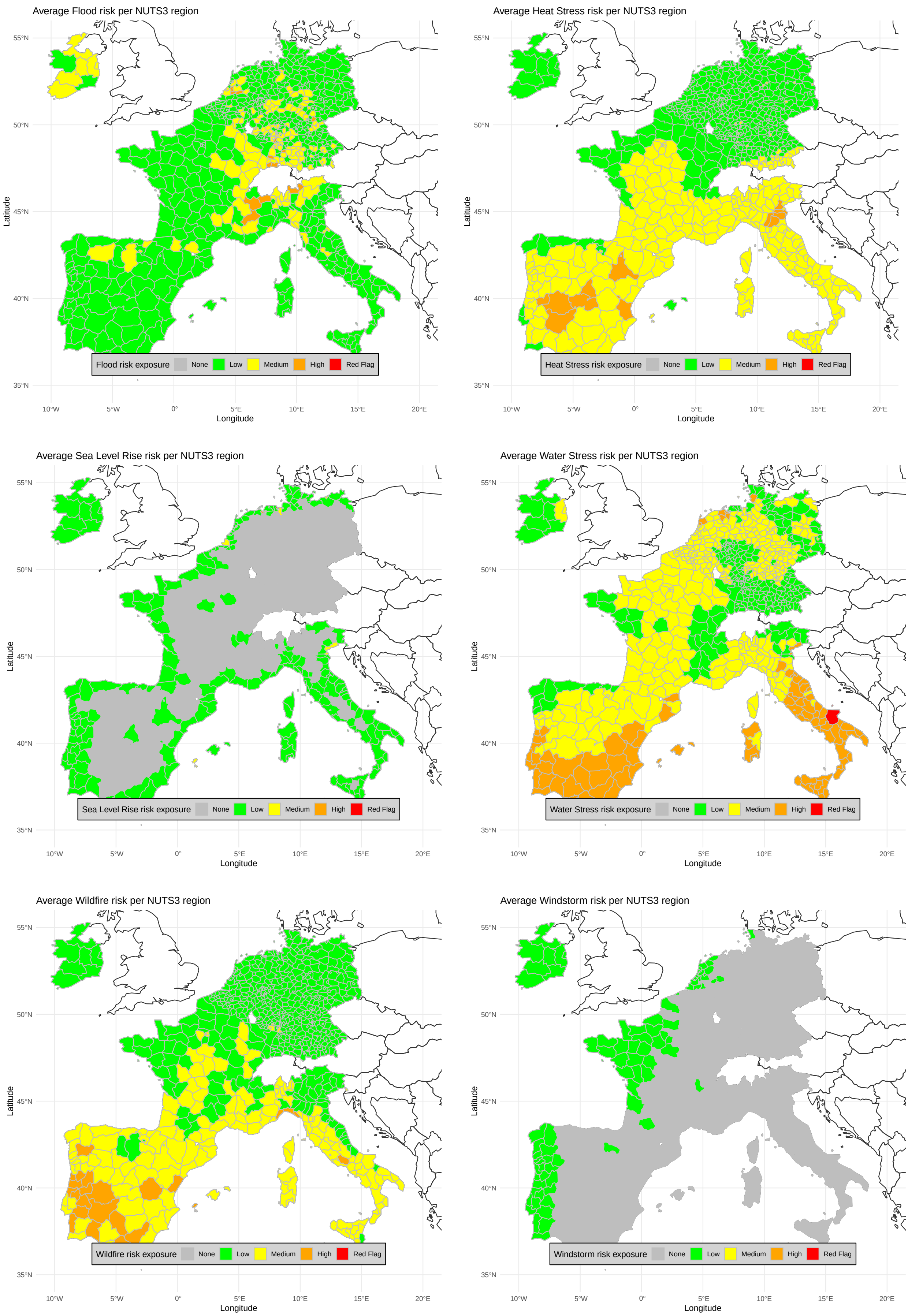

Figure 7: Index of number of climatic events (2020 = 1)

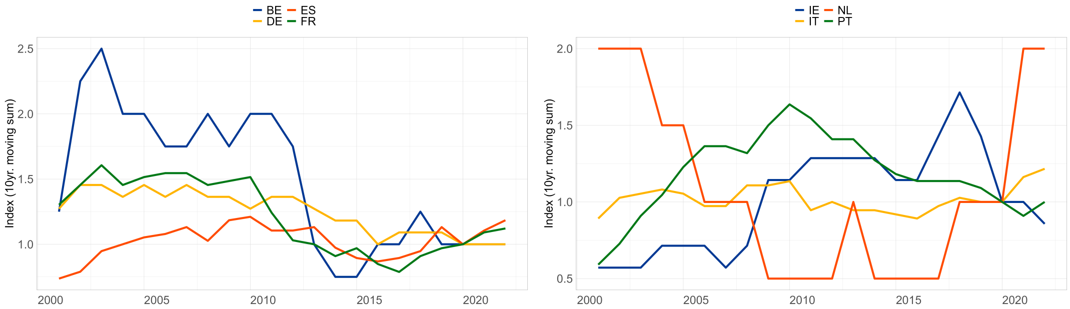

Table 17: Regressions with average dynamic climate risk scores for all lenders

	Interest Rate (pct)			
	No controls	Controls	Subperiods	Lender FE
	(1)	(2)	(3)	(4)
Dynamic Climate risk	0.02^{*} (0.01)	0.02^{**} (0.01)	-0.14^{***} (0.02)	-0.15^{***} (0.02)
Dynamic Climate risk × Loan issued (2013-2015)			0.17^{***}_{xxx} (0.02)	0.18^{***}_{x} (0.02)
Dynamic Climate risk × Loan issued (2016-2020)			0.24^{***}_{xxx} (0.03)	0.24^{***}_{xxx} (0.02)
Dynamic Climate risk × Loan issued after 2021			0.24^{***}_{xxx} (0.03)	0.26^{***}_{xxx} (0.03)
Controls		✓	✓	✓
Standard-Errors	NUTS2 region			
R^2	0.36612	0.44092	0.44902	0.54961
Observations	6,084,990	6,080,017	6,080,017	5,893,020
Country fixed effects	✓	✓	✓	✓
Year of origination fixed effects	✓	✓	✓	✓
SI or Lender fixed effects				✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

The LHS is the interest rate on a given loan in percentage points. To better interpret the interaction effects, a joint test of the interacted and uninteracted Dynamic Climate risk coefficients is also performed. The joint test has the H_0: Dynamic Climate risk+Dynamic Climate risk$\times B = 0$ and the results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, year of loan origination fixed effects, and lender heterogeneity fixed effects. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions. To account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW.

Table 18: Regressions with average dynamic climate risk scores for all Significant Institutions

	Interest Rate (pct)			
	All SIs	Adequate	s Inad	Inad
	(1)	(2)	(3)	(4)
Dynamic Climate risk	-0.20*** (0.02)	-0.21*** (0.04)	-0.15*** (0.04)	-0.05 (0.04)
Dynamic Climate risk × Loan issued (2013-2015)	0.20*** (0.02)	0.23*** (0.03)	0.13*** (0.03)	0.07* (0.04)
Dynamic Climate risk × Loan issued (2016-2020)	0.28^{***}_{xxx} (0.03)	0.29^{***}_{xxx} (0.04)	0.22^{***}_{xxx} (0.05)	0.01_{xxx} (0.04)
Dynamic Climate risk × Loan issued after 2021	0.30^{***}_{xxx} (0.04)	0.39^{***}_{xxx} (0.05)	0.19^{***}_{xxx} (0.04)	0.02_{xx} (0.04)
Controls	✓	✓	✓	✓
Standard-Errors	NUTS2 region			
R^2	0.55781	0.62292	0.52213	0.53542
Observations	4,605,541	1,602,346	2,872,333	130,862
Country fixed effects	✓	✓	✓	✓
Year of origination fixed effects	✓	✓	✓	✓
SI fixed effects	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

The LHS is the interest rate on a given loan in percentage points. To better interpret the interaction effects, a joint test of the interacted and uninteracted Dynamic Climate risk coefficients is also performed. The joint test has the H_0: Dynamic Climate risk+Dynamic Climate risk$\times B = 0$ and the results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. We split the sample into different subsamples. The 'All SIs' refers to all lenders in the EDW dataset that can be matched to a significant institution supervised by the SSM. 'Adequate' refers to a subset of these institutions that have at least an adequate level of climate risk management (as assessed in the TR). 'Inadequate' and 'Inadequate' refer to those in institutions that take climate risk into account somewhat inadequately and inadequately. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, year of loan origination fixed effects, and lender heterogeneity fixed effects. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions. To account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW.

Table 19: Regressions with average dynamic climate risk scores for all lenders

	Interest Rate (pct)			
	No controls	Controls	Subperiods	Lender FE
	(1)	(2)	(3)	(4)
Dynamic Climate risk	0.02*** (0.01)	0.02** (0.01)	0.04** (0.02)	0.03*** (0.01)
Dynamic Climate risk × Loan issued (2013-2015)			0.00_{xxx} (0.02)	-0.01_{xxx} (0.01)
Dynamic Climate risk × Loan issued (2016-2020)			-0.03 (0.02)	-0.02 (0.01)
Dynamic Climate risk × Loan issued after 2021			-0.03 (0.02)	-0.03** (0.01)
Controls		✓	✓	✓
Standard-Errors	NUTS2 region			
R^2	0.55924	0.48330	0.48337	0.57864
Observations	5,897,993	6,080,017	6,080,017	5,893,020
Country-Year of origination fixed effects	✓	✓	✓	✓
SI or Lender fixed effects	✓			✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

The LHS is the interest rate on a given loan in percentage points. To better interpret the interaction effects, a joint test of the interacted and uninteracted Dynamic Climate risk coefficients is also performed. In those cases where multiple effects are interacted, e.g. Dynamic Climate risk$\times B \times C$, the joint test has the H_0 : Dynamic Climate risk+Dynamic Climate risk$\times B$+Dynamic Climate risk$\times C$+Dynamic Climate risk$\times B \times C = 0$. The results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, year of loan origination fixed effects, and lender heterogeneity fixed effects. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions. To account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW.

Table 20: Regressions with average dynamic climate risk scores for all Significant Institutions

	Interest Rate (pct)			
	All SIs	Adequate	s Inad	Inad
	(1)	(2)	(3)	(4)
Dynamic Climate risk	0.02 (0.01)	0.04** (0.02)	0.00 (0.02)	-0.05 (0.04)
Dynamic Climate risk × Loan issued (2013-2015)	0.01_{xxx} (0.01)	-0.01_{x} (0.02)	0.01 (0.02)	0.06 (0.05)
Dynamic Climate risk × Loan issued (2016-2020)	-0.01 (0.02)	-0.04 (0.02)	0.01 (0.02)	0.01_{xxx} (0.04)
Dynamic Climate risk × Loan issued after 2021	-0.02 (0.01)	-0.05* (0.03)	0.00 (0.02)	0.02_{xx} (0.05)
Controls	✓	✓	✓	✓
Standard-Errors	NUTS2 region			
R^2	0.59045	0.65424	0.54446	0.54885
Observations	4,605,541	1,602,346	2,872,333	130,862
Country-Year of origination fixed effects	✓	✓	✓	✓
SI fixed effects	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Joint-Signif. Codes: xxx: 0.01, xx: 0.05, x: 0.1

The LHS is the interest rate on a given loan in percentage points. To better interpret the interaction effects, a joint test of the interacted and uninteracted Dynamic Climate risk coefficients is also performed. In those cases where multiple effects are interacted, e.g. Dynamic Climate risk$\times B \times C$, the joint test has the H_0 : Dynamic Climate risk+Dynamic Climate risk$\times B$+Dynamic Climate risk$\times C$+Dynamic Climate risk$\times B \times C = 0$. The results are only on the interaction coefficients and are denoted with x subscripts as indicated at the bottom of the table. We split the sample into different subsamples. The 'All SIs' refers to all lenders in the EDW dataset that can be matched to a significant institution supervised by the SSM. 'Adequate' refers to a subset of these institutions that have at least an adequate level of climate risk management (as assessed in the TR). 'Inadequate' and 'Inadequate' refer to those in institutions that take climate risk into account somewhat inadequately and inadequately. As controls, we consider the HH cost of borrowing, loan-to-value, debt-to-income, employment status and time to maturity at origination. The HH cost of borrowing is the monthly average of loans to households for house purchase from the MFI market interest rate statistics, i.e. not an EDW-derived quantity but rather a country-month benchmark rate. Credit risk controls are loan-to-value at origination, debt-to-income at origination, indicators of employment status, and time to maturity of the loan. In addition, we use country fixed effects to distinguish any local variation with respect to the LHS variable, year of loan origination fixed effects, and lender heterogeneity fixed effects. Standard errors (in parenthesis) are clustered at NUTS2 region to consider heterogenity within the regions. To account for lender heterogeneity, we use fixed effects that use either the SI group to which a given lender belongs - as mortgage rates tend to follow a standard procedure within a group - or the individual lender name as reported in the EDW.

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