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Heat projections and mortgage characteristics: evidence from the USA

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Abstract

Climate change is increasingly acknowledged as a fundamental risk to the stability of the financial system. The linkage between residential mortgage lending and local heatwave projections has hitherto received little attention in the climate finance discourse despite recognition of the detrimental effects of extreme heat on economic output measures. Through economic, demographic and other channels, future climate conditions can affect the housing market and, thus, the residential mortgage market. Moreover, the potential for contagion is high considering US residential mortgages' key role in financial cycles and cross-border effects. First, our paper furthers conceptual and empirical understandings of the nexus between future extreme heat and lenders' credit risk. Second, for the contiguous US states, we show that interest rates are higher and loan terms are shorter in areas forecast to experience a larger increase in the number of hot days over the coming decades after controlling for a range of factors. Rate spreads are higher still in areas where the number of hot days is projected to be extreme. It is lending from non-banks, rather than banks, that appears sensitive to the changing climate.

Keywords Climate change · Heat projections · Loan pricing · Non-banks

JEL Classification G21 · G23 · Q54

1 Introduction

Central banks and regulators have raised alarm bells over the financial stability implications of climate change and have voiced concerns about the extent to which climate risk is understood and appropriately managed at a firm level (Mandel et al. 2021). Evidence has been put forward suggesting informational and institutional barriers may hinder the accurate determination of climate-related risk in the US mortgage market (Keenan and Bradt 2020). Yet mortgages, and US mortgages in particular, deserve special attention because

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of their significant role in financial cycles (Jordà et al. 2016). Problems in US mortgage markets can quickly spill over to other US credit markets (Chan et al. 2016) and have cross-border effects (Horvath and Rothman 2021).

The extent to which mortgage markets factor in climate change may be a concern worldwide but particularly in countries, such as the USA, where borrowers' repayment willingness has been found to be strongly related to the collateral value. Evidence suggests that US real estate has yet to fully price in climate change. For example, the pricing in of sea level rise appears uneven at best (Baldauf et al. 2020) or non-existent (Murfin and Spiegel 2020), and over a fourth of the US population is still in denial about the changing climate (Howe et al. 2015) with a likely impact on their risk evaluation. And while the process of changing consumer preferences trickling into real estate markets may be gradual, we cannot rule out the possibility of brisker reassessments. According to Kahnemann and Tversky (1979), individuals incline towards simplifying their decision-making processes under risk and often disregard events of low probabilities. For example, there is some evidence that the crystallisation of natural disaster risk can—within a couple of years—substantially alter risk perceptions (Zhang and Leonard, 2019) and the salience of damage appears to play an important role (Garnache and Guilfoos, 2019). There is, therefore, a possibility in such countries that a potential house price fall due to climate change precipitates a drastic increase in non-performing loans. The impact on house prices and thus lenders may be swifter and more accentuated still in countries with high residential mobility rates—despite the downward trend US rates continue to be higher than those in other developed countries (Molloy et al. 2011). Failure to properly account for such risks raises the probability of disorderly movements in financial markets, of marked changes in credit provision with potential repercussions on the real economy (see discussions by Miles 2015 on the nexus between housing, mortgage and economic stability).

The extent to which financing conditions already incorporate local climate prospects is also informative for social inequality discussions because of the disadvantaged populations' presence in areas highly exposed to climate change (Islam and Winkel 2017; Ajibade 2019). Less favourable housing finance opportunities may contribute to climate gentrification—referred to as the displacement or entrenchment of populations brought about by how (expected) changes in the climate affect the property market, and resulting in an impact on the area's socio-economic mix (Keenan et al. 2018).

In this paper, we first investigate the conceptual underpinnings of the nexus between future heat and current residential mortgage lending, as heatwaves are set to increase in number, intensity and length (IPCC 2021). Thereafter, we present evidence that US mortgage rates are higher and loan terms shorter in areas most exposed to increases in heat though these are observable primarily in non-bank, rather than bank, lending.

While the effect of climate change on the mortgage market has been studied in the literature, there is a notable research gap with respect to the relationship between *heat projections* and mortgage lending. The studies in finance that rely on scientific climate projections study the impact of sea level rise projections (SLR) (e.g. Baldauf et al. 2020; Murfin and Spiegel 2020). Another strand of research focuses on mortgage lenders' reaction as climate change risk becomes more salient due to, for example, natural catastrophes or abnormal weather—rather than relying on scientific projections (Garbarino and Guin 2021; Duan and Li 2019). A US-downscaled version of global climate models represents the cornerstone of our study. According to the best of our knowledge, other authors of finance studies have not yet made use of these models' projected temperature data.

The paper is structured as follows. Section 2 provides a conceptual background and Sect. 3 reviews related literature. Section 4 describes the data and methodology, followed by the discussion of results and a battery of robustness checks in Sect. 5. Section 6 concludes.

2 Conceptual underpinnings

At a first glance, mortgage lenders do not appear particularly exposed to the risks of climate change since the time horizon of climate change spans decades—extending far beyond the seven to eight years' average life of the standard 30-year loan (Berman 2019) and past the first few years after origination when defaults on mortgages typically occur (Soyer and Xu 2010). Nonetheless, mortgage lenders are not immune to the risk. Most importantly, climate change-related physical destruction, local economy and demographic shifts or government measures need not occur, expectations and perceptions feed into house prices, and any change thereof may modify a number of mortgage portfolio characteristics such as prepayment rates and rates of arrears (Krainer and Laderman 2011).

Key to mortgage lenders' credit risk are the probability of default (PD), the loss given default (LGD) and the exposure at default (EAD). Perhaps the most obvious channel through which climate change can affect mortgage lenders is that of LGD. Any future change in expectations and perceptions about climate change may feed into house prices—and prevailing loan to values (LTV)—on a continuous basis. Moreover, natural catastrophes—where climate change is arguably a contributing factor and which are already happening—will affect real estate prices to the extent the risk is not priced in already (Duanmu et al. 2022). Importantly, Qi and Yang (2007) show that prevailing loan-to-value ratios are a key if not the key determinant of loss given default values.

In addition, in some countries such as the US, PD has been shown to be strongly related to house prices (Schelkle 2018). If house prices drop due to climate change-related reasons, borrowers may be more likely to walk away from their mortgages. Also, Gallagher and Hartley (2017) present some evidence of (at least a temporary) knock-on impact from natural catastrophes on debt delinquency rates and such effect may differ across households (Ratcliffe et al. 2020). A slowdown in the local economy, worsening health of residents, or a change in expectations thereof could also increase defaults. Indeed, Robertson et al. (2008) show that medical causes are one of the principal reasons behind mortgage foreclosures in the US.

The increase in heatwaves is projected to be significant and far from uniform (Collins et al. 2013), as can be seen in Fig. 1. On average counties in the contiguous United States are expected to experience a rise of 32 days by 2048 in the number of days a year during which maximum temperatures exceed 90°F in the medium carbon emission scenario. Indian River County, Florida, at one extreme is expected to see a rise of 90 days while no substantial change (1-day drop) is projected for Lincoln County, Oregon. Moreover, the rise in this metric is substantial even over shorter time horizons (28-day rise on average by 2038) and is even higher in the high emission scenario (38 days on average by 2048).

The housing market could be affected by such rises in temperature in a number of ways. Perhaps the most tangible effect relates to the risk of physical destruction: from wildfires brought about by higher temperatures and drier weather, for instance. But higher temperatures have also been found to lead to lower labour supply (Zhang and Shindell 2021), lower agricultural yields (Schlenker and Roberts 2009) and lower industrial output (Jones and Olken 2010), reduced firm profits (Addoum et al. 2022) and reduced economic growth (Burke et al. 2015). Importantly, research to date suggests that

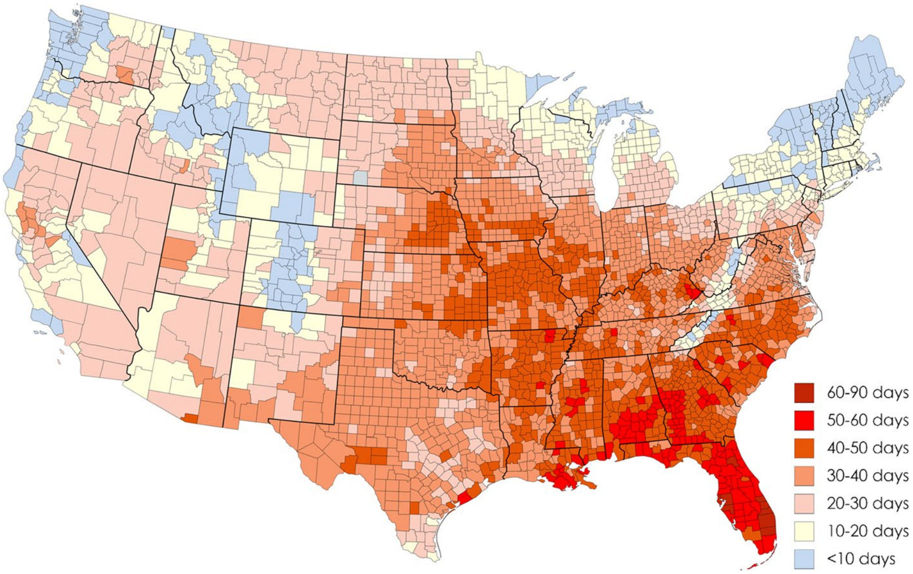

Fig. 1 Projected increase in the number of hot days. Notes: Hot is defined as when temperatures exceed 90 °F (32.2 °C). Medium carbon emissions (RCP 4.5) are assumed. 2048 versus 2003–2012 average (source of data: ACIS. Software: Mapchart.net)

even in developed countries, such as the USA, adaptation measures have achieved little in mitigating the negative effects of climate change on the macro economy (Kahn et al. 2019; Behrer and Park 2017). Extreme temperatures are also well understood to have negative health effects and lead to higher mortality and morbidity (Dong et al. 2015). The relationship between temperature and mortality exhibits nonlinearities especially at the extremes (Deschênes and Greenstone 2011). And while household-level adaptation has seen some important results in weakening the link between extreme heat and mortality in the past few decades, this is primarily driven by air-conditioning (Barreca et al. 2016). Air-conditioning under currently widespread technologies, however, should be insufficient in eliminating the impact of an increase in extreme heat on the real estate market either because of the increased costs air-conditioning represents (Kahn 2016) or due to the decreased utility hotter temperatures translates into, e.g. for lower income households unable to bear the costs of air-conditioning (Kahn 2016).

The (expected) climate of a local area may lead to shifts in local economic activity and demographics and, coupled with potential changes in the life expectancy and the health of residents, could influence the demand and supply of housing and housing finance. Through legislation, taxation, subsidies, rules on financing and zoning inter alia, central and local authorities have a profound influence on the housing market with measures potentially reflecting the changing public opinion (Howe et al. 2015).

There is some evidence suggesting that extreme heat is already increasing delinquencies and foreclosures as homeowners rationally update their expectations regarding climate change (Deng et al. 2021). The authors argue that the other possible explanations for the increase in credit events—liquidity constraints stemming from reduced labour supply and income, and altered decision-making abilities—play a less significant role.

Despite the scientific evidence on linkages, we know little about the extent to which lenders' macroeconomic, demographic and housing market expectations are shaped by climate prospects (see Sect. 3). If climate change does filter into such lender expectations, this need not be the result of an explicit incorporation of climate projections. Also, even if some lenders have explicit regard to climate change projections, this could happen at different stages in their complex decision-making processes—at the level of their risk models, real estate valuations, loan officer decisions, etc.—with lenders unlikely to be uniform in this respect. Current study employs large-sample statistical estimation and does not seek to disentangle the various channels.

If lenders foresee worsening prospects in certain areas, they have a menu of options as to how to react. They may withdraw from certain areas altogether, require an insurance, if available, reduce their exposure through securitisation, tighten criteria and adjust loan terms. In this paper, we investigate the latter—primarily interest rates but also the maturity of loans.

Importantly, we argue that although climate change risk is attracting increasing attention including from financial firms, it is not primary underwriters' and originators' primary area of expertise. Therefore, whether through data providers or directly, easily accessible, widely used projections that reflect the synthesised view of the scientific community would constitute an attractive option. As mentioned, such projections may explicitly or implicitly shape lenders' views on local economic, demographic and housing market prospects.

3 Literature review

Our study is related to several strands of the literature. A few recent papers document how lenders react to climate change. Most of these studies focus on past catastrophes or abnormal weather. Those that do rely on scientific projections study the risk of SLR. In contrast, our study relies on scientific *projections regarding future heatwaves*. Keenan and Bradt (2020) show that US local mortgage lenders are transferring SLR risk through securitisation. Ouazad and Kahn (2019) document the sale of riskier disaster area mortgages to government-sponsored enterprises (GSEs) in the aftermath of natural disasters. Garbarino and Guin (2021), however, find no reaction from mortgage lenders in England after the severe flood in 2013–2014 concerning local house price valuations, interest rates or loan amounts. Looking at bank lending to firms, Jiang et al. (2019) find higher interest rates to firms geographically exposed to SLR. Duan and Li (2019) show that abnormally high temperatures reduce mortgage approval rates and loan amounts and especially in counties where the population strongly believes in climate change or in counties that are most exposed to sea level rise. The authors attribute this to the human element within the traditional mortgage lending process: applications need to be approved by local loan officers. Regulators have also studied lender reaction. Berman's (2019) interviews with mortgage market participants indicate that the risk of flooding is primarily assessed through whether the property requires flood insurance due to its location in the 100-year floodplain at the initial transaction date. Hong et al. (2020) provide an overview of the broader literature on the pricing of climate risk by financial market participants.

By studying disparities in pricing behaviour with regard to climate change projections, we also contribute to the literature on lender heterogeneity. Fuster et al. (2019) show that in recent years the number and market share of non-banks have increased significantly. Buchak et al. (2018) and Seru (2019) discuss that compared to other lenders, non-bank fintechs, in particular, appear to rely on different information to set interest rates, exploiting advances in technology, possibly including digital footprint on social media. According to Fuster et al. (2019), they also process applications faster without higher default rates while Duan and Li (2019) point to less human involvement and less loan officer discretion.

Finally, our findings are interrelated with the literature on the capitalisation of climate change risk in asset prices, in particular real estate prices. This is because the extent to which property prices incorporate climate change affects lenders' climate risk, and lender behaviour may also influence real estate prices. Most recent studies that directly address the topic examine the impact of SLR on property prices and largely, though not unanimously, reach the conclusion that some pricing in has happened, cf. Bernstein et al. (2019), Baldauf et al. (2020) and Murfin and Spiegel (2020). Also, there is a rich body of literature studying the housing market impact of natural catastrophes which are expected to rise in number and impact due to climate change (e.g. Dillon-Merrill et al. 2018).

4 Data and methodology

For climate change projections, we use data from the Applied Climate Information System (ACIS) which is operated by the National Oceanic and Atmospheric Administration (NOAA) Regional Climate Centers. The data are a US-downscaled version of global climate models for the Coupled Model Intercomparison Project 5 (CMIP 5). The ACIS data are a synthesis of these different models and show projections for a medium (RCP4.5) and a higher carbon emission scenario (RCP8.5). Projections data from the ensemble mean of CMIP5 models have been used as inputs in macroeconomic projections by, inter alia, Harding et al. (2020), and are accessible to the broader public through the user-friendly Climate Explorer website created by US authorities. Unless indicated otherwise, we use the medium carbon emission scenario and define hot days as days during which maximum temperatures exceed 90 °F—a threshold also used by ACIS.

Loan-level mortgage data are sourced from the HMDA database of the Federal Financial Institutions Examination Council (FFIEC) —the most comprehensive publicly available data on US mortgages. The database includes rich information on borrower, property and loan characteristics. We use data for 2018 as from this year reporting institutions are required to disclose substantially more information and publicly available data include the rate spread of the loan. We focus on the "vanilla purchase mortgage" market segment.[1] We drop around 7500 observations that are likely erroneous (e.g. mortgage loan term at origination is just a few months, misalignment in state and county code), compared with a sample size of around 2 million. Both banks and non-bank financial institutions are required to meet HMDA reporting requirements if they had a home or branch office in a metropolitan statistical area and (for 2018 data) had assets in excess of USD 45 million at end-2017 in addition to meeting three further tests. In practice, most mortgage lending institutions are required to report their loans (Housing Assistance Council 2011).

We include a number of controls. Unemployment rate and annual average weekly pay by county are sourced from the US Bureau of Labor Statistics. We calculate county-level

[1] Single family, primary lien, not guaranteed by Federal Housing Administration, Farm Service Agency, US Department of Agriculture Rural Housing or Veterans Benefits Administration, not for commercial purposes, no open-end line of credit or reverse mortgage, without non-amortising features and where the loan purpose is home purchase and the loan has been originated.

house price volatility metrics from Federal Housing Finance Agency (FHFA) House price indices.

For credit scores, we use Fannie Mae and Freddie Mac databases. These two GSEs—created to support the housing market—publish loan-level detail on a large subset of the loans they purchase and include FICO credit scores. The GSEs can only purchase so-called conforming loans that are below the loan limit (USD 453 100 in 2018 for most of the US[2]) and meet other criteria such as LTV, debt-to-income ratio and credit score requirements.

We use crosswalk files from the US Department of Housing and Development (HUD) to map census tracts to first-three-digit zips. This is needed because HMDA, macroeconomic and climate data are on a census tract or county basis while Freddie and Fannie data are linked to first-three-digit zip codes. The crosswalk file includes information on the proportion of census tracts' residential addresses that map to the different zip codes.

We turn to the 2018 Yale Climate Opinion Survey for county-level public opinion about global warming (Howe et al. 2015). We use their county-level estimates for the proportion of adults who think global warming is happening.

Coastal counties in our study are defined as those included in National Oceanic and Atmospheric Administration's (NOAA) sea level rise database. Data on the number of natural disasters are sourced from FEMA and correspond to Presidential disaster declarations which enable the US President to provide supplemental federal disaster assistance to disaster-struck areas. We turn to NOAA Comparative Climatic Data for average historical afternoon humidity data.

Online Resources provide an overview of the samples used in the study.

We use the following OLS equation for the rate spread baseline specification for approved loan *i* by lender *l* in county *j*:

$$\text{Rate spread}_{ijl} = \alpha + \beta_0 \text{Climate variable1}_j + \beta_1 \text{Climate variable2}_j + \gamma \text{Controls}_{ijl} + \epsilon_{ijl} \tag{1}$$

where Climate variable1 measures the projected increase in the number of hot days. Climate variable2 is a dummy for counties with a projected extreme number of hot days, defined as the top 1% of counties which are forecast to experience at least 165 hot days per annum. Arguably, the current number of hot days (*level*)—correlated with the future number of hot days—already has an impact on macro-economic and demographic factors which is not the focus of our study (therefore we do not include a simple level variable). We include Climate variable2 because temperatures have been shown to have non-linear effects at the extremes (e.g. Deschênes and Greenstone, 2011). The coefficients of interest are β_0 and β_1. The rate spread is defined as the loan's annual percentage rate (APR) minus the survey-based national average prime offer rate (APOR) for a comparable transaction as of the date the interest rate is set. The rate spread is reported by lenders and the FFIEC provides HMDA reporters with a rate spread calculator. Controls include those that are standard in the literature—borrower, property, loan-level and macroeconomic variables. We control for what action the lender takes with the mortgage (most importantly whether it sells it on to GSEs) because Hurst et al. (2016) show that this has an impact on pricing. In addition, competition amongst lenders and local housing market risks—measured via the house price volatility—are controlled for in the regressions as Feng (2018) has shown that they influence lending standards. We cluster standard errors by county and we include a dummy for each lender. We acknowledge that some selection bias may arise if lenders

[2] The FHFA updates conforming loan limits each year to take account of changes in average home prices.

reject more applications in areas more exposed to increased future heat. This bias would, however, be negative and the coefficient of our climate variable would be even greater absent such bias (Supplementary Material Appendix 1).

We use a similar equation to estimate the probability of a sub-standard loan term (dependent variable) but use probit regressions instead of OLS.

To study heterogeneity, we examine whether non-banks' rate setting differs from that of banks. We use interaction terms between the climate variables and the non-bank dummy. In these specifications, we omit the individual lender dummies as they would cause multicollinearity issues. Instead, we introduce a variable that intends to proxy the lender's general rate-setting behaviour: some lenders may typically set higher rates due to higher overheads, for example, irrespective of the climate. We use the mean rate spread—the loan's annual percentage rate (APR) minus the average prime offer rate (APOR) for a comparable transaction as of the date the interest rate is set—on other mortgages originated by the same lender for this purpose. All other variables are identical to those used in Eq. (1).

Although OLS or panel regression is frequently used in the literature to study mortgage characteristics, some scholars have noted the problem arising from endogeneity: rate spreads and other mortgage characteristics such as LTVs are not set independently. Indeed, it is possible that lenders require higher down payments from riskier borrowers in addition to setting higher interest rates. This may cause bias in our estimated coefficients. Therefore, as a robustness check, we follow the IV/2SLS approach as applied by Ambrose et al. (2018).

5 Results and discussion

5.1 Baseline results

Table 1 specifications 1–3 present regression results from Eq. (1) without the second climate variable. Our results suggest that mortgage rates are higher in counties where the number of hot days is projected to rise by more, comparing 2048 with 2003–2012 historical averages and controlling for a range of factors. Results are statistically significant. Comparing an area with no projected increase in the number of hot days with an area for which the average of 32-day rise is projected suggests this effect alone corresponds to a 2 basis points difference (0.06*32) in the rate spread (specification 1). The effect is not economically insignificant considering the mean rate spread in our sample of 47 bps. Results are robust to the definition of hot day—applying a threshold of 90 °F or 95 °F both produce statistically significant results with a coefficient of 0.06–0.1 (specifications 1 and 3). Similarly, results are robust to whether the medium emission scenario (specification 1) or the high emission scenario (specification 2) is used on account of the strong correlation between the two scenarios in the next three decades.

Specification 4 shows results from Eq. (1) also including the second climate variable. Beyond the relationship with the projected increase in hot days, rate spreads are on average 8 bps higher in counties expected to experience an extreme number of hot days, again controlling for a range of factors. Regressions looking ahead to 2028 or 2038 instead of 2048 yield broadly similar results for all four specifications (untabulated).

Table 2 presents probit regression results of climate projections on the probability that the term of the mortgage is shorter than the standard 30 years. Eight percent of our sample has a contractual maturity shorter than 30 years. The first climate variable's positive

Table 1 Baseline regression results of climate projections on the rate spread

	(1)	(2)	(3)	(4)
Diff2048_RCP4.5_90F (days)	.0578** (.0287)			.0722*** (.0234)
Diff2048_RCP8.5_90F (days)		.0501** (.0234)		
Diff2048_RCP4.5_95F (days)			.096*** (.0248)	
Extreme no hot days dummy				8.3784*** (2.1632)
Controls	Yes, see notes	Yes, see notes	Yes, see notes	Yes, see notes
Observations	1,994,036	1,994,036	1,994,036	1,994,036
R-squared	.4077	.4077	.4078	.4083
Lender dummies	Yes	Yes	Yes	Yes

Notes: Rate spread is defined as the loan's annual percentage rate (APR) minus the average prime offer rate (APOR) for a comparable transaction as of the date the interest rate is set. The independent variables of interest are the climate variables: in specification 1, the projected increase in the number of days with maximum temperatures above 90 °F, 2048 compared with the 2003–2012 average. The medium (high) emission scenario is used in specification 1 (specification 2). Specification 3 is similar to specification 1 but uses 95 °F instead of 90 °F as the threshold for hot days. Specification 4 is also based on specification 1 but includes an extreme number of hot days dummy—defined as the top 1 per cent of counties and equivalent to at least 165 days with maximum temperatures above 90 °F. The control variables (debt-to-income ratio, applicant old age, applicant race, ethnicity, sex, combined LTV, loan amount, loan term, secondary residence dummy, lenders' action with mortgage, unemployment, average weekly wage, house price volatility, local competition) and the constant are omitted from the table for presentational purposes. Local house price volatility is measured as the maximum minus the minimum of the county-level FHFA house index, adjusted for inflation, between 2000 and 2017. Local competition is measured as the share of the top 10 lenders in a county. Standard errors in parentheses are clustered at the county level. ***$p<.01$, **$p<.05$, *$p<.1$

Table 2 Probit regression results: probability that term of loan < 30 years

	Loan term < 30 years			Marginal effects at means		
	Coeff	St. Error	Sign	dy/dx	St. error	Sign
Diff2048_RCP4.5_90F (days)	.00580	.00043	***	.00058	.00004	***
Extreme no of hot days dummy	.17994	.02622	***	.02052	.00337	***
Controls	Yes, see notes					
Observations		1,981,643				
McFadden's pseudo-R^2	0.1869					
Lender dummies	Yes					

Notes: The independent variables of interest are the climate variables: (i) the projected increase in the number of days with maximum temperatures above 90 °F, 2048 compared with the 2003–2012 average and (ii) an extreme number of hot days dummy—defined as the top 1% of counties and equivalent to at least 165 days with maximum temperatures above 90 °F. The control variables (debt-to-income ratio, applicant old age, applicant race, ethnicity, sex, combined LTV, loan amount, rate spread, secondary residence dummy, lenders' action with mortgage, unemployment, average weekly wage, house price volatility, local competition) and the constant are omitted from the table for presentational purposes. Standard errors in parentheses are clustered at the county level. ***$p<.01$, **$p<.05$, *$p<.1$. Dydx for factor levels is the discrete change from the base level coefficient and marginal effect can be interpreted as the higher the projected rise in hot days, the higher the probability that the loan term is less than 30 years, controlling for the other variables. The probability of a sub-standard loan term is 4.5% in counties where the projected increase in the number of hot days is 24.5 days (the 25th percentile) and all other variables are at their means, whereas it is 5.4% for counties where the projected increase in the number of hot days is 40.4 days (75th percentile) (untabulated). Thus, the effect of a higher value for the climate variable: at the top of the interquartile range instead of the bottom of it, ceteris paribus, equates to a 1-percentage point higher probability of a sub-standard loan term. If the county is projected to experience an extreme number of hot days, this effect alone, equates to a 2 percentage point higher probability of a sub-standard term loan, assuming all variables are at their means. The coefficient of this second climate variable is also highly statistically significant. Directionally OLS regressions yield similar results.

5.2 Banks and non-banks

Next, we turn to examine whether non-banks' rate setting differs from that of banks in respect of climate change projections. Non-banks' share of mortgage lending has grown in an unprecedented manner in the past decade from under 30% in 2008 to around 60% in 2018 (Seru 2019). Importantly, the vast majority of non-banks are new as only a handful survived the financial crisis a decade ago (Lux and Greene 2015). This suggests that compared to banks, non-banks face less issues stemming from legacy systems and processes, and mindsets that resist change. In principle, therefore, one might expect a greater openness at non-banks towards innovation, including related to new data sources, when designing their credit scoring systems and processes. Indeed, Seru (2019) notes that data science has enabled underwriters to access new sources of information to gauge applicants' creditworthiness. We use Buchak et al. (2018)'s classification list of the largest bank and non-bank lenders. This covers 45% (40%) of the loans in our HMDA sample by value (number). The authors define banks as depository institutions. For the purposes of gauging the openness to new data sources, we believe that the distinction between banks and non-banks is more important than the distinction between fintechs and other non-banks. Relatedly, the latter distinction is much more subjective, as noted by Buchak et al. (2018). Fuster et al. (2019), for example, classify a firm as fintech if the borrower can obtain a preapproval without the need of physical presence or talking to a loan officer. To this end, the authors manually initiate a mortgage application at each of the largest non-banks. Fuster et al. (2019) acknowledge that this is just one element of the fintech model. For our purposes, however, it is the use of new information that matters—irrespective of the extent of digitalisation of the application and underwriting process. For example, according to Buchak et al. (2018), United Shore and Fairway Independent, amongst the largest non-banks, would be classified as a non-fintechs. Yet according to media reports, United Shore is well-recognised amongst mortgage brokers for its technology platform, having invested heavily in technology (Reindl 2020). Similarly, according to NerdWallet (2019), Fairway Independent has used technology to streamline the closing process but a physical presence of 15 min or less is needed for signing—which is irrelevant for our purposes.

Table 3 shows that non-banks do indeed charge higher rates in areas where the projected number of hot days is greater, controlling for a number of factors. Specifically, a 1-day higher projected increase in the number of hot days is associated with a 0.14 bps higher rate charged by non-banks. Extreme hot temperatures projections, as measured by

Table 3 Regression: the impact of non-bank lenders and climate projections on the rate spread

	Coef	St.Err	Sig
Diff2048_RCP4.5_90F	.0069	.0319	
Diff2048_RCP4.5_90F* non-bank	.1398	.0263	***
Extreme no of hot days	3.7144	1.179	***
Extreme no of hot days* non-bank	10.0425	2.1743	***
Non-bank	– 10.2861	1.0946	***
Lender rate spread	.779	.0177	***
Controls	Yes, see notes		
Observations	837,560		
R-squared	0.3909		

Notes: The rate spread is defined as the loan's annual percentage rate (APR) minus the average prime offer rate (APOR) for a comparable transaction as of the date the interest rate is set. The independent variables of interest are the climate variables and the interaction terms with the non-bank lender dummy. The two climate change projection variables are (1) the projected increase in the number of days with maximum temperatures above 90 °F, 2048 compared with the 2003–2012 average and (2) an extreme number of hot days dummy—defined as the top 1% of counties and equivalent to at least 165 days with maximum temperatures above 90 °F. We use Buchak et al.'s (2018) classification list of the largest bank and non-bank lenders. This covers 45% (40%) of the loans in our HMDA sample by value (number). The authors define banks as depository institutions. The control variables (debt-to-income ratio, applicant old age, applicant race, ethnicity, sex, combined LTV, loan amount, loan term, secondary residence dummy, lenders' action with mortgage, unemployment, average weekly wage, house price volatility, local competition) and the constant are omitted from the table for presentational purposes. Lender rate spread proxies lender efficiency and profit margin and is calculated as the mean rate spread on the other loans originated by the same lender. Standard errors in parentheses are clustered at the county level. ***$p < .01$, **$p < .05$, *$p < .1$

the number of hot days, equate to 10 bps higher rates on non-banks' lending compared to banks' loans.

We reach similar conclusions if we distinguish between independent mortgage companies, big and small banks, credit unions and affiliated mortgage companies following Consumer Financial Protection Bureau (2020). Only independent mortgage companies' interaction term with the climate variable is positive and statistically significant (untabulated).

5.3 Robustness checks

Some scholars have noted that loan interest rates and loan characteristics such as LTV or maturity are determined endogenously (e.g. Donaldson and Wetzel 2018), raising questions about the bias of coefficients gained through OLS. To respond to such concerns, similarly to Ambrose et al. (2018), we use IV/2SLS. Following the logic of Ambrose et al. (2018), we use the mean LTV and the mean loan term of each lender—calculated excluding the mortgage in question—as instruments for the specific mortgage's LTV and loan term. A lender's general behaviour regarding its preferred LTVs and loan terms may have an influence on the specific mortgage's LTV or maturity but would not directly affect the interest rate on the mortgage in question. Tests on the first-stage regressions indicate that the instruments are sufficiently strongly correlated with the instrumented variables.

We rerun a plethora of regressions using 2SLS which confirm the direction and high statistical significance of the relationship between the rate spread and the climate variables after controlling for a number of factors (Table 4). All specifications show that an additional day in the projected increase in hot days for 2048 raises the rate spread on mortgages. The coefficient in specification 1 (0.16) suggests a stronger relationship than OLS results (coefficient of 0.06 in Table 1). Specification 2 documents that non-banks raise their rates more in response to higher values of the climate variables—directionally identical to the relationship uncovered in Table 3.

We also examine whether it is climate change beliefs rather than climate change projections that drive our results. While one may expect areas subject to a larger increase in the number of hot days in the future to be more cognisant of climate change, this is not the case. In fact, the Pearson bivariate correlation coefficient (-0.25 with a p-value of 0.00) at the county-level between (i) the proportion of adults who think global warming is happening and (ii) the projected rise in the number of days in which maximum temperatures exceed 90 °F suggests a moderate negative relationship. The negative relationship is consistent with the correlations reported by Murfin and Spiegel (2020) in respect of exposure to relative SLR and beliefs or worries about global warming as well as with the idea of geographic sorting and homophily. We control for climate change beliefs in alternative specifications for Table 3 (untabulated), gaining further confirmation that climate change projections have a statistically significant impact on rate spreads.

While HMDA data provides rich detail on a range of borrower and mortgage characteristics, one notable variable missing is borrowers' credit score such as FICO. The coefficients of our climate variables gained thus far could be particularly biased if the geographical pattern of the credit score values had some similarities with that of the climate variables. FICO scores are available in Fannie Mae and Freddie Mac databases as part of the information they disclose on the loans they purchase from sellers. Just under half (44%) of loans in our filtered HMDA sample is indicated as having been sold to Fannie or Freddie within a year of origination. While a significant part of the market, the GSEs can only purchase loans meeting a number of criteria—therefore, these loans cannot be seen as representative of the mortgage market as a whole. Also, Fannie and Freddie data link to the first-three-digit zip code rather than counties—the basis on which climate data are available—and do not contain information on borrowers' age, sex, race and ethnicity.

To incorporate FICO scores in our analysis, we match loan-level data from Fannie and Freddie with HMDA data on a best endeavours basis and perform regression analysis. Chang and Koss (2019) discuss that matching GSE and HMDA data poses significant challenges and have led researchers to start exploring the potential in AI. For example, the originating company—of which there are thousands—could feature under a slightly different name in the disparate datasets. In our exercise, we match based on the loan term (months), interest rate (to three decimal places), debt-to-income ratio, the loan amount and the first-three-digit zip. We use the HUD crosswalk files to map census tracts in HMDA to first-three-digit zip codes. While census tracts are much more granular than the first three digits of the US Postal Service zip codes—73,470 census tracts versus 908 first-three-digit zips in the 2018 crosswalk file—14% of census tracts do not map unambiguously to the aforementioned zips. In specification 1, we link these tracts to the first-three-digit zips accounting for the greatest proportion of the census tract's residential addresses. In specification 2, we drop observations from these tracts. We create two sub-samples from HMDA data: loans indicated as sold to Fannie and loans indicated as sold to Freddie. From these,

Table 4 2SLS: Impact of climate projections on the rate spread

	(1) HMDA 2sls	(2) HMDA 2sls non-bank	(3) FFmatch1 2sls	(4) FFmatch2 2sls
Diff2048_RCP4.5_90F	.1611*** (.0305)	.1967*** (.0396)	.312*** (.085)	.3708*** (.101)
Diff2048_RCP4.5_90F* non-bank		.0781*** (.0302)		
Extreme no of hot days dummy	11.6808*** (3.7452)	8.7413*** (1.9874)	14.7618*** (4.1741)	18.2167*** (4.9077)
Extreme no of hot days* non-bank		10.8754*** (2.2838)		
Non-bank		−9.3325*** (1.143)		
FICO score			−.0153** (.007)	−.0137* (.0074)
Lender rate spread	.9026*** (.0083)	.8472*** (.0245)	.5514*** (.0321)	.5599*** (.0388)
Controls	Yes, see notes			
Observations	1,993,944	837,560	27,694	23,314
McFadden's pseudo-R-squared	.1508	.1235		

Notes: The rate spread is defined as the loan's annual percentage rate (APR) minus the average prime offer rate (APOR) for a comparable transaction as of the date the interest rate is set. The instrumented variables are the combined LTV ratio and the loan term. The mean LTV and the mean loan term of other loans originated by the same mortgage lender are used as instruments. All specifications include two climate variables: (1) the projected increase in the number of days with maximum temperatures above 90 °F, 2048 compared with the 2003–2012 average and (2) an extreme number of hot days dummy—defined as the top 1% of counties and equivalent to at least 165 days with maximum temperatures above 90 °F. Specification 2 (3) also includes interaction terms between the climate variables and lenders' geographical concentration (a non-bank dummy). Specifications 1 and 2 are run on the baseline dataset; specification 3 encompasses identified banks and non-bank firms only based on Buchak et al.'s (2018) classification list of the largest lenders. In order to include the FICO score, specifications 4 and 5 use a small subset of baseline data that has been matched on a best endeavours basis with Freddie and Fannie data. Where tract-zip mapping is ambiguous, the census tract is assigned to the first-three digit zip containing the highest proportion of the tract's residential addresses (specification 4) or the related observation is dropped (specification 5). The control variables (debt-to-income ratio, applicant old age, applicant race, ethnicity, sex, combined LTV, loan amount, loan term, secondary residence dummy, lenders' action with mortgage, unemployment, average weekly wage, house price volatility, local competition) and the constant are omitted from the table for presentational purposes. Standard errors in parentheses are clustered at the county level. ***$p<.01$, **$p<.05$, *$p<.1$

Table 5 Regressions: subsamples without the hottest and the least hot counties

	(1) Drop + & − 10 pc	(2) Drop + 10 pc	(3) Drop − 10 pc	(4) Drop + 20 pc	(5) Drop − 20 pc
Diff2048_RCP4.5_90F (days)	.115*** (.0231)	.1041*** (.022)	.0604* (.0312)	.0788*** (.0288)	.0603* (.0363)
Controls	Yes, see notes				
Observations	1,546,605	1,664,277	1,876,364	1,527,119	1,619,502
R-squared	.3984	.3964	.4098	.3983	.4161
Lender dummies	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the regression results of climate projections on the rate spread: the loan's annual percentage rate (APR) minus the average prime offer rate (APOR) for a comparable transaction as of the date the interest rate is set. The independent variables of interest is the climate variable: the projected increase in the number of days with maximum temperatures above 90°F, 2048 compared with the 2003–2012 average. Specifications 1–5 use subsamples by dropping loan contracts pertaining to the counties which experienced the highest and/or lowest number of days with maximum temperatures above 90 °F on average between 2003 and 2012. Specification 1 drops the highest and lowest 10%, specification 2 (3) drops the highest (lowest) 10 percent, whereas specification 4 (5) drops the highest (lowest) 20%. The control variables (debt-to-income ratio, applicant old age, applicant race, ethnicity, sex, combined LTV, loan amount, loan term, secondary residence dummy, lenders' action with mortgage, unemployment, average weekly wage, house price volatility, local competition) and the constant are omitted from the table for presentational purposes. Standard errors in parentheses are clustered at the county level. ***$p < .01$, **$p < .05$, *$p < .1$

as well as the Fannie and Freddie datasets, we first drop observations where our matching criteria would not uniquely identify a loan—resulting in dropping 25%, 23%, 4% and 4% of observations from the four datasets, respectively. We then match the HMDA "sold to Fannie" data with Fannie data and undertake a similar separate exercise in respect of Freddie data. In both cases, the majority of data do not perfectly match based on our criteria. Matched Fannie and Freddie data are then combined. A comparison of the matched dataset with our original HMDA filtered dataset is available in the Online Resources.

Table 4 specifications 3 and 4 show 2SLS regression results based on these matched data. Given the difficulties in the matching process and the possibility of erroneous matches, the interpretation of these results must be undertaken with care, the analysis serving more as a robustness check than providing standalone results. That said, results are directionally in line with previous findings, climate variables are highly statistically significant and FICO scores are also statistically significant. Simple Pearson correlation coefficients suggest no significant correlation between FICO scores and our climate variables.

A further concern could arise from the relationship between future projections and current climate conditions. For example, if it is the areas that are already the hottest—and thus the most unpleasant or the least favourable from a macroeconomic standpoint—that are projected to experience the highest rise in heat, then higher interest rates may simply reflect current conditions rather than expectations about the future. In order to rule out that this explanation is driving our results, we remove loan contracts pertaining to the 10 or 20% of counties that experienced the most and/or least number of hot days from our sample and rerun the baseline regression (Table 5 specifications 1 to 5). In addition to loan contracts from other states, dropping 20% of the hottest counties removes about 80% of the loans originated in Florida. The coefficients of projected number of hot days remain positive and statistically significant in these subsamples. The impact of the expected increase in

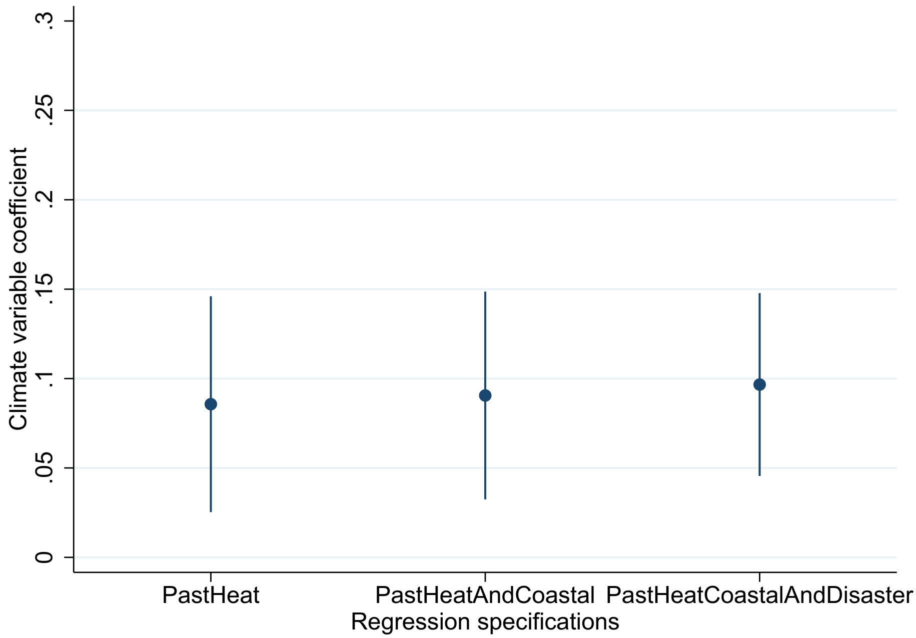

Fig. 2 Climate variable coefficient under specifications with different past climate controls. Notes: This figure presents the regression results of climate projections on the rate spread: the loan's annual percentage rate (APR) minus the average prime offer rate (APOR) for a comparable transaction as of the date the interest rate is set. It shows the independent variable of interest only which is the climate variable: the projected increase in the number of days with maximum temperatures above 90 °F, 2048 compared with the 2003–2012 average. Specification 1 (past heat) controls for the recently experienced average number of hot days. In addition, specification 2 controls for whether the loan was originated in a coastal county. Specification 3 adds controls for the recently experienced number of natural disasters to specification 2. For the past heat (past disaster) ordinal variable, counties are classified into 6 categories based on their average number of hot days between 2003 and 2012 (based on the number of natural disasters between 2001 and 2017) as follows: the first 4 groups include 20% of counties each. To provide more granularity for the hottest counties (counties with the highest number of recent disasters), groups 5 and 6 include 10% of counties each. The control variables are debt-to-income ratio, applicant old age, applicant race, ethnicity, sex, combined LTV, loan amount, loan term, secondary residence dummy, lenders' action with mortgage, unemployment, average weekly wage, house price volatility, local competition. Standard errors are clustered at the county level. The dots represent the point estimate while the lines correspond to the 95% confidence intervals

heatwaves on mortgage rate spreads appears more significant—both statistically and economically—if we exclude the 10% of counties which have experienced the greatest number of hot days in recent years. This may reflect some adaptation—at the level of the local economy or households—already underway in currently hot areas.

To provide further confirmation that current climate conditions or recently experienced weather phenomena are not the drivers of our results, we add controls for the recently experienced average number of hot days and the number of natural disasters to our baseline regression. Additionally, we control for whether the loan was originated in a coastal county to address the concern that coastal counties may experience a different set of risks, for example related to sea level rise. All specifications continue to confirm at a high statistical significance that mortgage rates are higher in counties where the number of hot days is projected to rise by more (Fig. 2).

Arguably, the impact of hot temperatures on the human body is exacerbated amid more humid conditions (Sherwood 2018). In the absence of county-level humidity projections akin to ACIS data on extreme heat, we perform a simple check in which we split the baseline sample into two: loan contracts pertaining to the historically more humid half of the states and those pertaining to less humid states using data from a central weather station in each state on afternoon humidity. This simple test suggests that rate spreads on mortgages from historically more humid states are the ones driving the uncovered relationship between rate spreads and the increase in hot days (untabulated). A more in-depth examination of humidity's role in how the risk of extreme heat is incorporated in financial markets could be a worthwhile future research angle.

If the housing market has been most buoyant in areas that are forecast to see the largest rise in extreme heat and lenders are raising interest rates in such areas in line with an expectation of market normalisation, our results might mistakenly attribute the impact to the direct or indirect effect of warming temperatures. Moreover, such rate increases may be most prominent amongst non-bank lenders, as non-bank lenders are often seen as more sensitive to market cycles. We test this alternative hypothesis in Supplementary Table 4: our overall conclusions regarding mortgage rates and heat projections remain unchanged. The interaction term between non-banks and recent market heat is statistically insignificant and the climate variables' coefficients are similar in size to those reported in Tables 1 and 3.

We also check for undue influence from local time-varying economic conditions: if the near-term local macroeconomic outlook that is independent from long-term climate prospects is correlated with hot temperate projections (Supplementary Material Appendix 2). Results continue to show at a high level of statistical significance that interest rates are higher in areas more exposed to an increase in heat.

Finally, we examine whether the interest rate premium rises with the length of the loan. If lenders are concerned about increases in extreme hot temperatures, this may be accentuated at longer time horizons over which projections show a greater increase and which are also subject to higher uncertainty. Indeed, the statistically significant, positive coefficient of the interaction term between the climate variable and the loan term is consistent with this interpretation (Supplementary Table 5, specification 4). The result is not at odds with our findings for the length of the loan in Table 2. For areas most exposed to the rising number of hot days, we thus see shorter maturities or higher interest rate premia at longer maturities.

6 Conclusion

Our study outlines a number of channels through which future extreme heat can affect lenders originating mortgages today. At a financial system level, a key question is the extent to which financial markets are pricing climate risks properly—anticipating risk events and efficiently discounting them. The better markets are at pricing the risk today, the lower the probability of extreme price movements and bankruptcies in the future. There is a widespread belief that financial market participants are still underestimating the risks, leading to financial stability concerns.

Considering a range of controls and potential sources of bias, we find that larger projected increases in the number of hot days during the coming decades are associated with higher rate spreads and an increased probability that loan terms are shorter than the standard 30 years. In counties projected to experience an extreme number of hot days, both the rate spread and the probability of a short loan term are higher still. While somewhat reassuring from a financial stability point of view and adding to the findings of other studies on the mortgage and housing market, there are at least three points to make. First, while in aggregate mortgage rates do appear to reflect heat prospects, this is less observable in one (large) segment of the mortgage market, notably bank lending—of potential concern to supervisors and financial stability authorities. A reason for this could be that compared to the much newer non-bank sector, banks are—on average—slower to apply additional and novel datasets in their processes. Second, our study does not seek to inform on the optimal level of rate spreads or loan terms with respect to the risk of global warming—an important area for future research. Third, while incorporation of future climate prospects in financing conditions alleviates financial stability concerns, in the absence of appropriate policy responses, it may carry undesirable social implications, especially if effects grow over time. Alongside increasing costs in exposed areas which are more burdensome for the poor, relocation driven by worse risk-adjusted returns may be hampered by a lack of resources for certain households (Keenan et al. 2018). Worse(ning) financing conditions and the ensuing local economic effects (Di Maggio et al. 2017) could thus have uneven effects on the population across socio-economic lines even prior to substantial losses linked directly to weather hazards, especially if it is the disadvantaged population that is geographically most exposed to the changing climate (Alizadeh et al. 2022),

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Author contribution Author 1 contributed to the study conception and design, material preparation, data collection, analysis and wrote the manuscript. Author 2 provided important comments at each stage of the process. All authors read and approved the final manuscript.

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Data availability The datasets analysed during the current study are available in the following locations:

- http://builder.rcc-acis.org/
- https://ffiec.cfpb.gov/data-publication/
- https://www.bls.gov/
- https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx
- https://capitalmarkets.fanniemae.com/credit-risk-transfer/single-family-credit-risk-
- transfer/fannie-mae-single-family-loan-performance-data.
- https://www.freddiemac.com/research/datasets/sf-loanlevel-dataset
- https://www.huduser.gov/portal/datasets/usps_crosswalk.html
- https://climatecommunication.yale.edu/visualizations-data/ycom-us-2018/
- https://coast.noaa.gov/slrdata/
- https://www.fema.gov/disaster/declarations
- https://www.ncei.noaa.gov/products/land-based-station/comparative-climatic-data

Declarations

Competing interests The authors declare no competing interests.

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