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CLIMATE CHANGE AND RESIDENTIAL MORTGAGE LENDERS

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1. INTRODUCTION

Climate change is amongst the most important phenomena in the modern history of mankind giving rise to momentous current and projected future challenges. Climate scientists leave no doubt: our global climate system is warming, the number of days with extremely hot temperatures is increasing, and geographic patterns of precipitation are changing markedly – with some areas experiencing more, others less precipitation than before (Collins et al., 2013). No dimension of our lives are immune to related changes: the shape of our societies, our businesses, our political establishments and our financial system is unlikely to remain untouched.

This dissertation focuses on one segment of the financial system: mortgage lenders. 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 & Bradt, 2020). Yet mortgages, and US mortgages in particular, deserve special attention because 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 & Rothman, 2021).

The extent to which mortgage markets factor in climate change, may be a concern worldwide but particularly in countries, such as the US, 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 & 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 & Leonard, 2019) and the salience of damage appears to play an important role (Garnache & Guilfoos, 2019). There is, therefore, a possibility in countries such as the US 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).

In theory, lenders may take comfort in adaptation measures. But some manifestations of climate change may be inherently difficult to mitigate through adaptation measures – fighting sea level rise, for example, may be particularly challenging in areas with vast coastlines and low populations. And so far, the effectiveness of adaptation measures falls far short of eliminating the negative effects of climate change, even in developed countries such as the US (Kahn et al., 2019; Behrer & Park, 2017).

If lenders are concerned about the risk, a variety of reactions are theoretically possible – such as withdrawing from certain areas, increasing interest rates, requiring more collateral, applying stricter terms and conditions or (in the US) selling their most exposed mortgages to government-sponsored enterprises (GSE) for securitisation.

All of these options, as the option of not reacting, have wide-ranging implications on financial stability, the real economy, society, environmental sustainability and potentially public finances.

First, it is important to see that the potential consequences to a lender could easily gain a systemic dimension. A number of lenders could simultaneously experience hardships as awareness about climate change risk increases or the risk crystallises. Also, due to the intertwined nature of financial markets, losses at one firm can spread through both counterparty effects and through market valuations of assets. 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).

Second, the extent to which financing conditions already incorporate local climate prospects is also informative for social inequality discussions. Reviewing evidence on the adverse effects of climate change (which is more numerous in developing countries), for these countries Islam and Winkel (2017) highlight the disadvantaged populations' presence in areas highly exposed to climate change. In the US, Emrich and Cutter (2011) acknowledge the difference in resilience to climate hazards across socio-economic lines and identify vulnerable populations in the southeastern United States. 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). With the potential to mitigate such an effect, the extent to which GSEs step in and the policies they follow in high climate risk areas, may have an influence on environmental inequalities across socio-economic lines. GSE involvement could form part of a carefully managed policymaker strategy.

Third, a transfer of climate risk to GSEs should be of policy interest especially if the risk is backed by the taxpayer or is mitigated through risk sharing between borrowers in areas due to experience lower and higher rates of climate change. Such a risk sharing would not only mean cross-subsidisation between these households, but may reduce appreciation of climate risk and provide suboptimal incentives – such as by encouraging new construction in areas prone to flooding in the future.

Importantly, the relationship between climate change and the financial sector (including mortgage finance) is not one-way, the financial sector is not just at the receiving end. Through financing activities, financial system actors can have an indirect impact on the process of climate change, depending on the sustainability of their activities (Boros, 2020). Properties exhibit large differences in terms of their environmental impact (Lützkendorf, 2018) and location is key in this respect. Both the environmental footprint of a building and the financial cost of its operation can vary significantly from one location to another, and in light of climate change, it would be desirable that the characteristics of buildings financed by mortgage lending today match the climate of the area in the future. There appear to be shortcomings in this respect. For example, the most effective protection against heat available on a large scale today – air conditioning – is environmentally unsustainable (Lundgren-

Kownacki et al., 2017), drawing attention to the spatial distribution of construction and mortgage lending as well as the issue of technological advancement. Also, in many US states housing construction rates are up to two to three times higher in zones which are at risk of flooding due to rising sea levels as compared to less at-risk neighbourhoods (Climate Central, 2019), even though protecting against sea level rise is difficult and costly (Leatherman, 2018). In addition, construction in such areas increases the risk of flooding, as the weight of buildings can cause tangible subsidence of the ground surface (Parsons, 2021).

A useful line of enquiry, therefore, is to understand the extent to which financial market participants are reacting to future climate-related challenges. Despite the significant practical importance, however, research on the topic in relation to residential mortgage lending is scarce. 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 & 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 & Guin, 2021; Duan & Li, 2019). A US downscaled version of global climate models represents the cornerstone of my dissertation. According to the best of my knowledge, other authors of finance studies have not yet made use of these models' projected temperature and precipitation data.

While many of the dilemmas discussed in the dissertation are applicable worldwide, available data supports the study of the contiguous United States. Moreover, the country's geographical dimensions allow sufficient diversity in exposure to climate change and hence lenders have the potential to differentiate.

It is beyond the scope of the dissertation to study all possible forms of lender reaction. Instead, through case studies I present evidence on: i) overall lending amounts ii) rejection rates, iii) interest rates and iv) securitisation to GSEs. Similarly, the detailed study of each and every dimension of climate change is not the objective of the dissertation. Within climate change, I mostly study heatwaves (extreme heat) but also flood risk (risk of high levels of precipitation) and drought risk (risk of low levels of precipitation). Importantly, sea level rise risk – the most-studied dimension of climate change in the housing and mortgage market literature – is beyond the scope of the dissertation.

Based on the literature, I expect limited incorporation of such climate change risks in overall lending volumes and interest rates. That said, I hypothesise that some lenders with a more open approach will incorporate this risk into their pricing, especially at the extremes of climate change risk. Also, securitisation to GSEs may be an emerging form of risk mitigation.

Turning to the results, the dissertation explores the conceptual linkages between future climate and lenders' credit risk and draws a conceptual linkages map. The dissertation then investigates how climate change is shaping the US residential mortgage market. An important conclusion is that some reaction from mortgage lenders is observable. Loans are slightly more expensive and loan terms shorter in areas most exposed to increases in heatwaves. Another way in which lenders are mitigating their risk is by selling their climate-riskiest loans to GSEs which largely ignore climate change risks in their framework. The offloading of the risk to GSEs has in fact intensified in the more recent years of the study (2016-2019). Looking at the volume of lending to future heat-prone areas, however, suggests climate change considerations play second fiddle to business rationale. Mortgage volumes in the counties most exposed to future heat reflect the higher concentrations of the country's population and economic output (relative to the land share of these areas). That said, lenders do reject proportionately slightly more mortgage applications in the counties that are expected to be the hottest even after controlling for a number of factors. Turning to heterogeneity, results suggest that non-banks are ahead of banks in their reaction to climate change.

Given the considerable lending volumes in the climate-riskiest areas as well as common exposure across many residential mortgage lenders to the same climate change dimension, further investigation by financial stability authorities would be useful to ascertain whether the extent of risk incorporation is sufficient, in particular by banks. As for the transfer of climate risk to GSEs, more analysis needs to be undertaken to ascertain who is ultimately backing the risk – is it the taxpayer (if GSEs are left with the risk), households in areas less exposed to climate change (e.g. if GSEs apply the same pricing and terms and conditions irrespective of climate exposure this could amount to cross-subsidisation) or other market participants (e.g. through the use of credit transfers)? Each carries important policy implications. Finally, results give some urgency to considerations on how to manage the social impact of changing conditions in housing financing in the most climate-exposed areas. GSE policies could form part of such strategy.

I obtain results by using difference-in-difference estimators, matching (synthetic, nearest neighbour), linear regressions with OLS estimation, pooled regression with OLS estimation, probit regression, IV 2SLS and fixed effects panel regression in addition to descriptive statistics and rates.

The dissertation is structured as follows. Section 2 provides a general background on US mortgages and the broader climate finance literature. Ahead of diving into the literature closely related to the research questions, the chapter also presents the conceptual background on the channels through which mortgage lenders are exposed to climate change. Section 3 provides an overview of the data used. Sections 4 to 6 each present a case study in which I examine a loan market variable in conjunction with a climate change exposure metric. Each of these case studies relies heavily on articles already published or under review as below. Final deliberations are presented in the Conclusion section.

Case study 1:

Baranyai, E., & Banai, Á. (2022). Feeling the heat: Mortgage lending and central bank options. *Financial and Economic Review, 21*(1), 5-31.

Case study 2:

Baranyai, E., & Banai, Á. (2022). Heat projections and mortgage characteristics: Evidence from the USA. *Climatic Change, 175*, 14. (Q1 Journal)

Case study 3:

Baranyai, E. (2023). Are mortgage lenders offloading climate exposure to government-sponsored enterprises? Working Paper.

2. LITERATURE REVIEW AND BACKGROUND

2.1. Background on lenders and the mortgage market in the US

Banks are critical to both the economy and the financial system (Allen et al., 2019). They facilitate borrowing and lending in the economy by ameliorating informational problems between those that need funds and those that wish to lend funds, and monitor proper use of funds lent. They also enable customers to optimise consumption across time – achieved through maturity transformation (which, however, makes them exposed to liquidity risk). Another one of banks' many key functions and that of financial markets more broadly is the enabling of risk-sharing. Banking thus supports growth in the economy.

Non-banks, which are financial institutions without a full banking licence and which are not allowed to take deposits from the public (Worldbank, 2016), are also a significant source of credit in the US (Degerli & Wang, 2022; Dela Cruz & Villaluz, 2023) and thus have also become key to the economy and the financial system.

The past few decades have seen many changes in the US lending landscape (DeYoung, 2019). The banking industry has consolidated with the number of commercial banks decreasing and the largest banks increasing in size. Alongside large commercial banks, which provide high-volume retail services to US customers and corporate and investment banking services globally, small community banks serve US retail and small business banking customers (DeYoung, 2019). Following the near disaster of the sector in 2008-09 and the accompanying government bailouts, the regulatory framework was tightened. Separately, new technologies have emerged. This has, on the one hand, transformed and made banking more efficient and, on the other, contributed to increased competition from non-banks in the financial sector. Non-banks' share has seen a steady rise in recent years across the US, including in retail mortgages (Degerli & Wang, 2022) and non-bank loan origination has surpassed that of banks (Dela Cruz & Villaluz, 2023).

Before an overview of the US mortgage market, it is worth briefly mentioning the basic characteristics of a mortgage (Weiss & Jones, 2017). These are:

- the principal (the amount)

- the term (the length)
- the schedule for repayment (lump sum or monthly instalments)
- the interest rate.

The lender may set other terms and conditions such as applying a prepayment penalty for early repayment. In the US the most common type of mortgage has a term of 30 years, has its rate fixed – that is, the interest rate does not change during the term of the loan, and is self-amortising (Weiss & Jones, 2017). The latter means that every payment is identical in value over the loan term, a mixture of interest and principal (the proportion of interest decreases over time). Although the contractual maturity of loans tend to be 30 years, most mortgages are paid off much earlier, in less than 10 years (Berman, 2019) via one of three means. A borrower may make extra payments and pay off earlier (prepayment). Alternatively, it is quite common to refinance loans in the US. Refinancing means that a borrower takes out a new mortgage and uses it to repay the old mortgage. The new mortgage is typically more advantageous to the borrower. It may, for example, have lower interest rates. Finally, a mortgage will also be repaid when the borrower sells the property.

A typical deposit (called downpayment in the US) in the US mortgage market is 20% of the value of the property (Weiss & Jones, 2017). But borrowers short of this amount may purchase an insurance either privately or from a government agency that seeks to subsidise a certain population segment. The three government agencies that provide insurance are: Federal Housing Administation, Department of Veteran Affairs and US Department of Agriculture. Government-insured loans are excluded from my samples.

Interest rate-setting on mortgages is not a straightforward process (Bhutta et al., 2020). Typically the loan officer or mortgage broker – who may act as an intermediary between the borrower and a range of bank and non-bank lenders – consults their rate sheet. This latter is regularly updated, at least once a day and often sources information from the secondary market – the securitisation market. The rate sheet provides price information based on the category of the loan (e.g. loans conforming to GSE requirements, in excess of GSE size limits (jumbo loans), guaranteed by a government agency, etc.). Rates will also reflect loan and borrower characteristics such as credit scores, LTV, loan amount, property location, property type and the purpose of the loan (e.g. purchase or renovation). If loans are to be sold on for securitisation, guarantee fees from GSEs are also taken into account (more on guarantees and securitisation below). Further costs increase rates such as compensation to the loan officer and mortgage broker. Lender margins are added on top which, in turn, reflect lenders' operational efficiency and the competitive landscape. Bhutta et al. (2020) also show that the borrower's financial sophistication and shopping activity can reduce rates.

Rates are set in conjunction with so-called points which can be used to reduce origination costs (Bhutta et al., 2020). In other words, a slightly higher interest rate can reduce origination costs. Also, there may be exceptions if, for example, there is also an offer from a competitor.

There are a few major risks associated with mortgage lending (Weiss & Jones, 2017). Most obviously, lenders run credit risk as borrowers may not repay according to the terms of the loan. Delinquency refers to being behind on payments at which point the borrower and the lender may agree on a modification of the payment schedule and other terms. Mortgage default is a step beyond delinquency. At this point foreclosure or short sale kicks in. Both involve the sale of the property. Rules vary across states and in some states these processes do not remove all of the debt if the borrower owed more than the amount recuperated through the sale of the property (Weiss & Jones, 2017).

In the US prepayment risk is also very much in focus. Borrowers typically repay as interest rates are falling (Fuster et al., 2013) which also means lower returns to the lender on new investments or lending. Funding risk arises from the maturity mismatch typical in lending: financing lending activities with shorter term sources of funding (Weiss and Jones, 2017). These risks may or may not be borne by the originator.

These risks are managed through multiple means such as responsible underwriting standards, credit loan diversification (credit limits), risk-based pricing, interest rate derivatives or asset-liability management of fixed and adjustable rate products.

Another way originators may manage risks is through the sale of loans in the secondary market. This can be in the form of whole loans (transfer of mortgage to the new owner) or in the form of securitisation (Weiss & Jones, 2017). In essence, securitisation involves pooling together a high number of loans. Mortgage-backed securities (MBS) are issued to investors on the back of the cash flows from these loans. Apart from liquidity that comes with creating securities from loans, another advantage of securitisation is tranching: the creation of securities with different risk and return profiles. The highest-rated tranches have the lowest risk and return.

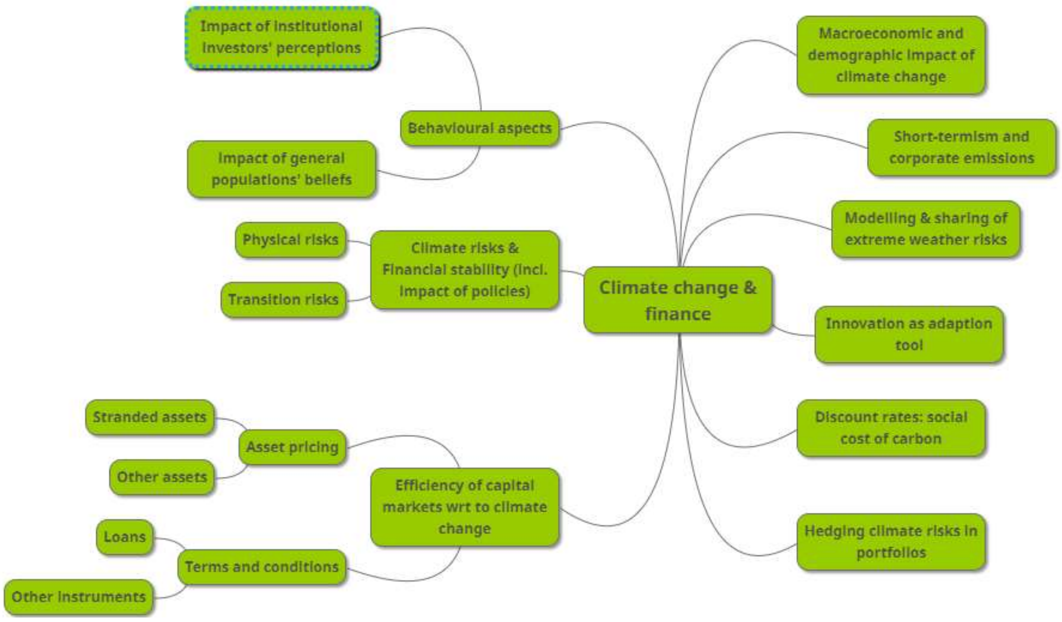
There are three main forms of MBS securitisation in the US (Weiss & Jones, 2017). The largest segment is that of Fannie Mae and Freddie Mac, two government agencies created about 5 decades ago to help the housing market (Fuster et al., 2013). Fannie and Freddie purchase mortgages and either securitise them (providing a guarantee to investors in the process) or keep them on their books (Weiss & Jones, 2017). The MBS of Ginnie Mae – a government corporation – includes mortgages guaranteed or insured by the government. Finally, private-label securitisation typically includes mortgages that do not meet the critera of the government agencies, related to, for example, size or credit standards.

Securitisation enables the shift of risk from originators (lenders) to other parties (Weiss & Jones, 2017). In Fannie Mae, Freddie Mac and Ginnie Mae securitisations, it is these government agencies that bear the credit risk while investors bear interest rate risk. In private label securitisations investors are exposed to credit risk (as well as interest rate risk) though some form of credit enhancements, such as insurance from a private insurance, can mitigate exposure.

2.2. Climate finance literature: an overview

Climate finance is a burgeoning area within the academic literature (Hong et al., 2020; Battiston et al., 2021) with various notable strands of research. Figure 1 provides an overview.

Figure 1 Overview of climate finance research



Source: Author

Probably one of the earliest strands of the literature on climate finance concerns the incorporation of climate risk into macrofinance models (Hong et al., 2020). The foundation of these research efforts can be traced back to Nordhaus (1977), a seminal paper that focused on the link between climate change and the real economy. The initial paper was followed by more papers from the author, mainly exploring questions on optimal climate change mitigation (Nordhaus, 1977, 1991, 1992). Later models incorporated stochasticity related to physical and economic processes, uncertainty and risks (Kolstad, 1993; Manne & Richels 1992; Nordhaus, 1994; Nordhaus & Popp, 1997; Kelly & Kolstad, 1999; Weitzman, 2001, 2009; Lemoine & Traeger, 2012; Golosov et al., 2014).

An important question with considerable controversy is the appropriate discount rate and the social cost of carbon (Hong et al., 2020; Gollier, 2013). Discount rates are at the centre of the cost-benefit analyses economists perform to evaluate investment opportunities. Discount rates can be seen as the price of time. Gollier (2013) explains how discount rates lie at the heart of the disagreement between ecologists and economists: investments with returns in the very distant future (say 200 years) would be advised against on a cost-benefit basis using the usual level of discount rates. Investment decisions would be driven by short-term benefits. Research is being undertaken both on the ideal level of discount rates and the term structure of the discount rate. Using lower levels of discount rates for longer time horizons may be socially efficient (Giglio et al., 2015). There are a number of ways a socially efficient discount rate can be estimated. The discount rate observed on financial markets conveys information about society's appetite to transfer wealth to future generations. An alternative way is to observe the marginal rate of return on productive capital and new projects are to be embarked upon if the return is larger than that on alternative projects. A third way is to view the discount rate as the return on savings that preserves welfare. As investment lowers current consumption, the reduction in welfare today should be compensated by increased welfare in the future.

Gollier (2013) argues that avoiding the use of discount rates (or applying zero discount rates) goes against the interest of future generations as it diverts capital away from better uses. Rather, it is important that all non-monetary impacts are appropriately valued. A strand of research estimates the social cost of carbon (Barnett, Brock, and Hansen, 2019). There are at least two sources of major uncertainties that such efforts need to address. One concerns the uncertainty surrounding how climate change affects human welfare, the other how human activity affects the climate.

Other authors investigate the impact of temperature, precipitation and windstorms on economic activity. Dell et al. (2024) provide an overview of the studies. The effect is non-linear and heterogeneous across types of locations and there is a number of channels that link the weather to the economy: agriculture and labour productivity, energy demand, health, conflict, pollution levels, rate of food spoilage, prevalence of vector-borne diseases, etc.

An interesting strand of research focuses on how corporate short-termism and financing constraints result in suboptimal climate change investment outcomes. Shive and Forster (2019) show that public firms are more likely to incur Environmental Protection Agency penalties and are more likely to pollute than private firms, suggesting ownership structure and horizon considerations have a role to play.

The investigation of the link between climate change and financial stability risks is recent (Battiston et al., 2021) and encompasses two main areas. First, risks from climate change and the transition to low-carbon economy on the financial system. Second, the incorporation of climate change in asset valuation and portfolio risk management.

A particular point in investigations on financial stability is the emphasis on the interconnectedness of market participants and the focus on the system level: individually optimal decisions may lead to suboptimal outcomes overall. My dissertation also applies this focus. Integrating climate change which is non-linear with tipping points in macroeconomic models is challenging. Battiston et al., 2021 discusses the increased use of stock-flow consistent and agent-based models to investigate the impact of climate change (e.g. Lamperti et al., 2019; Monasterolo and Raberto, 2018; Dafermos et al., 2017; Bovari et al., 2018).

A number of papers, including this dissertation, investigate the extent to which capital markets incorporate climate change. Hong et al. (2019) study stock markets and drought risk which is very damaging for crops and food companies. The authors find that droughts have a statistically and economically significant (negative) impact on profitability ratios yet much of the effect is not priced in stock markets. A portfolio strategy shorting food stocks in drought areas generates sizeable returns over the three decades up to 2015. Krueger et al. (2019) surveyed global institutional investors who thought equity valuation in some sectors fail to fully incorporate climate change risks.

Specific markets and financial market participants have also been examined – a further strand of research my dissertation is closely related to. Shashwat et al. (2018) find that professional money managers in disaster-struck regions overreact to disasters and reduce exposure much more to disaster area stocks than others. This is not driven by superior information and is costly. The authors link the behaviour to the salience bias. A number of authors examine the real estate market which I will discuss in more detail in other subchapters (Baldauf et al., 2018; Bernstein et al., 2019; and Murfin & Spiegel, 2018). Similarly, I will present an overview of the literature on lenders' climate change induced behaviour in a separate subchapter.

Arriving at strong conclusions on how climate change is priced in stock markets has thus far been hampered by the lack of standardised information on what constitutes a climate-friendly investment (Battiston et al., 2021). Environmental, Social and Governance ratings are not consistent across providers, many are based on selfreported data and methodologies differ. That said, studies focusing on different aspects of ESG investing – financial performance, use as a hedge, ESG investor characteristics, measuring corporate responsibility etc. – have been on the rise.

Another important and relevant strand of the literature studies climate change beliefs and risk perception. A seminal piece of work in this regard is the Yale Climate Climate Opinion survey (Howe et al., 2015; Marlon et al., 2022). As part of the project, regular and detailed surveys are conducted at a granular spatial level within the US. The survey also forms the basis of international assessments of climate change beliefs (Leiserowitz et al., 2022) and related research on the importance of climate change beliefs on asset pricing (Baldauf et al., 2020) and central banking (Baranyai et al., 2024). There is some evidence that climate change beliefs react to environmental factors. Choi et al. (2018) show that climate change beliefs are shaped by the weather: abnormally high temperatures lead to more focus on climate change. This has a financial market impact as retail investors reduce exposure to carbon-intensive firms.

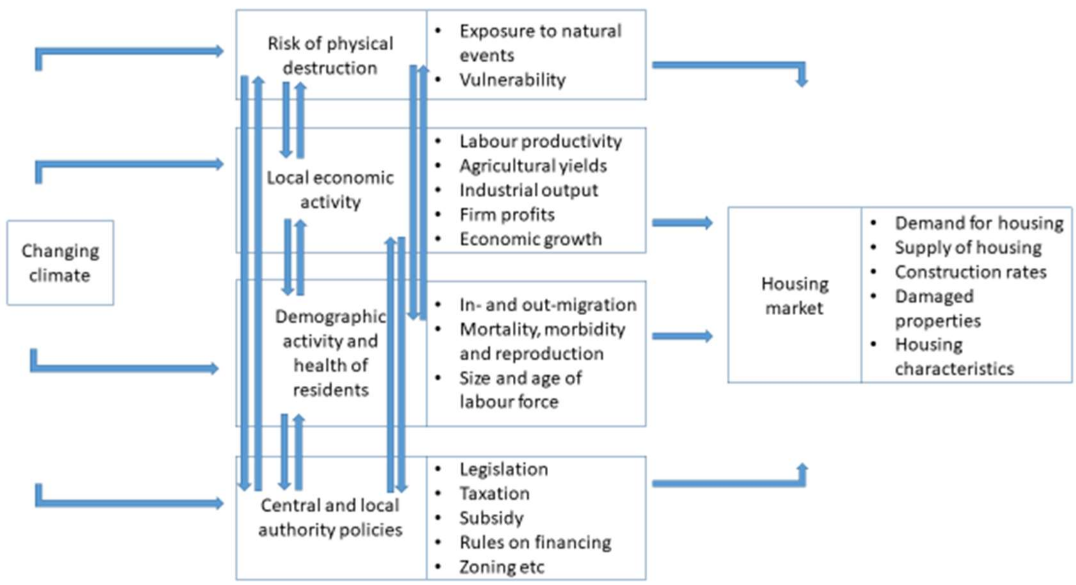
As concerns about climate risk rise, so does interest in how climate risk can be hedged. Engle et al. (2019) use textual analysis of newspapers to extract news on climate change and build portfolios that are hedged against changes in climate change news. If the variation in climate change news follows underlying climate change risk, the authors' approach can be seen as providing a hedge against climate change risk. Andersson et al. (2016) develop a dynamic investment strategy for passive investors to hedge against climate risk. The authors claim there is no sacrifice of financial returns by using the decarbonized indices proposed in their paper. At the same time, according to the authors, such an approach protects against the future price impact of the incorporation of CO2 emissions in asset prices.

Finally, a lightly-researched area concerns that of corporate and financial innovation and adaptation driven by climate change. Miao and Popp (2014) study the corporate innovation of drought-resistant crops that was brought about by an increase in droughts. One can also view green bonds as a form of financial innovation related to climate change (Baker et al., 2018).

2.3. Bank lending and climate change: conceptual underpinnings

At a first glance, mortgage lenders don't 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-years loan (Berman, 2019) and past the first few years after origination when defaults on mortgages typically occur (Soyer & 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 (Figure 2), and any change thereof may modify a number of mortgage portfolio characteristics such as prepayment rates and rates of arrears (Krainer & Laderman, 2011).

Figure 2 Climate change and the housing market: channels and interactions



Source: Author

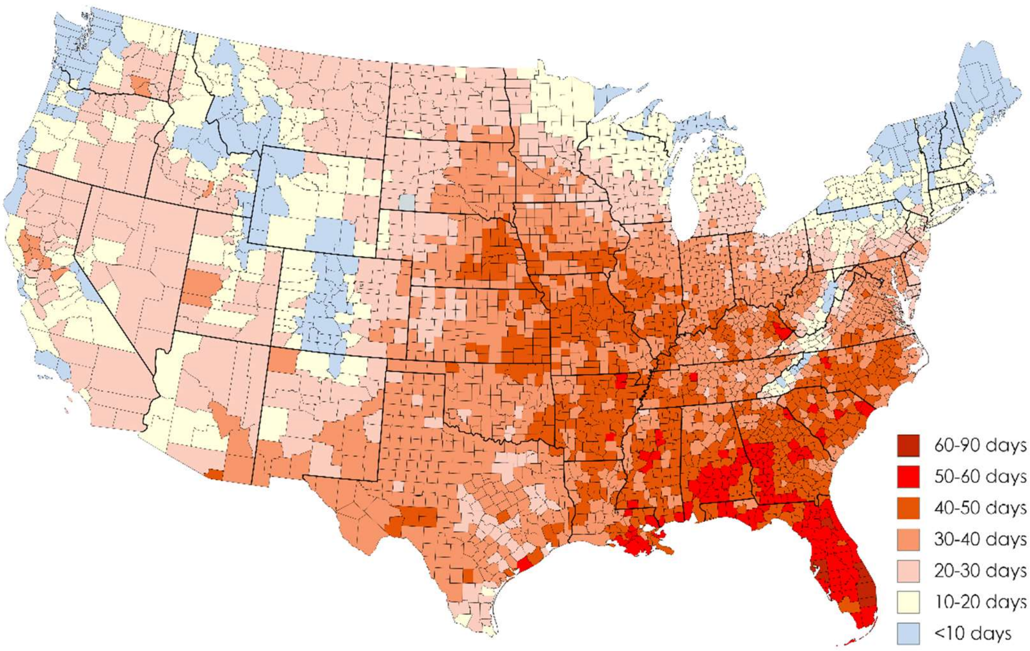
Key to mortgage lenders' credit risk are the probability of default (PD), the loss given default (LGD) and the exposure at default (EAD). Perhaps the most obvious channel through which climate change can affect mortgage lenders is that of LGD. Any future change in expectations and perceptions about climate 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.

I will now provide more detail on the channels using heatwaves as an example. The channels through which the other dimensions of climate change affect the housing market and ultimately residential mortgage lenders follow a similar logic.

The increase in heatwaves is projected to be significant and far from uniform (Collins et al., 2013), as can be seen in Figure 3. 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 days' rise on average by 2038) and is even higher in the high emission scenario (38 days on average by 2048).

Figure 3 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.

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 & Shindell, 2021), lower agricultural yields (Schlenker & Roberts, 2009) and lower industrial output (Jones and (Olken, 2010), reduced firm profits (Addoum et al., 2018) and reduced economic growth (Burke et al., 2015). Importantly, research to date suggests that even in developed countries, such as the US, adaptation measures have achieved little in mitigating the negative effects of climate change on the macro economy (Kahn et al., 2019; Behrer & 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 (Deschenes 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, 2020) 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, 2020).

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.

Beyond credit risk on loan portfolios, lending to climate change-exposed areas may also carry reputational risk, and may also spill over into other forms of risk to the business, such as funding risk.

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. 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.

Importantly, I 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.

2.4. Climate change and lender behaviour

Notwithstanding the general scarcity of research on lender reaction to climate change, there are a few recent papers that do examine this question. These studies typically focus on the change in lenders' behaviour once climate change risk becomes salient due to, for example, natural catastrophes or abnormal weather (Garbarino & Guin, 2021; Duan and Li, 2021; Ouazad & Kahn, 2019). Results from these studies do not allow us to reach a universal conclusion regarding lenders' climate change concerns. Garbarino and Guin (2021) find that following the 2013-14 severe flood event in England lenders did not decrease property valuations in line with local prices, nor did interest rates or loan amounts on repeat mortgage transactions fall. Cortés and Strahan (2017) document an increase in overall US mortgage lending to affected areas after natural disasters which they link to banks' aim to protect rents in their core markets coupled with an increase in loan demand to rebuild damaged property.

In contrast, Ouazad and Khan (2019) argue that the option value of GSE securitisation increases following disasters. The authors exploit the fact that GSEs do not update their rules following hurricanes that cause multi-billion dollar damages, while these events may provide new information on flood risk to lenders. They also exploit the discontinuity in loans that are sold to GSEs with respect to their size. The authors not only document a bunching of loans just below GSE limits (at all times) but observe that following natural disasters the share of these loans (and thus sale to GSEs) increases. The authors argue that loans just below the GSE limits are in fact riskier than those just above and therefore their results cannot be interpreted as a retreat from riskier mortgages to safer loans. 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.

While past or current events may carry some information regarding future developments, the weather and climate phenomena have been well-documented to experience non-linearities (Ashkenazy et al., 2003), with potential for feedback loops between climate factors, economic and demographic developments, mitigation and local adaptation actions (Collins et al., 2013). Projections for the future thus cannot be seen as simple extensions of the past. Climate projections data confirm that it is not necessarily the hottest areas that are forecast to see the highest rise in heatwaves. My research links the non-SLR dimensions of future climate change more directly to current lender behaviour. This enables a more straightforward interpretation regarding lenders' climate change risk assessment, free from conflating factors such as lender reactions reflecting changed local conditions or results reflecting organisational psychology and decision-making following disasters.

In the area of SLR risk, studies linking climate change projections and lender behaviour have been carried out. Keenan and Bradt (2020) show that US local mortgage lenders are transferring SLR risk through securitization. Looking at bank lending to firms, Jiang et al. (2019) find higher interest rates to firms geographically exposed to SLR.

There have been a few forward-looking analyses that examined the volume of today's activities in terms of climate exposure. The most relevant example is the analysis of housing construction rates according to flood risk exposure (Climate Central, 2019), also taking into account the climate scepticism of people living in areas exposed to climate change (Barrage & Furst, 2019).

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.

2.5. Climate change and property values

With property serving as collateral in mortgage transactions, lenders' risks related to sudden moves in collateral prices would be mitigated if house prices perfectly incorporated the expected changing prospects of the local area and the property. In the opposite case, concerned lenders may look for other risk mitigation options such as the modification of terms or securitisation. 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). But available evidence fails to convince of a widespread and uniform incorporation of all climate change risks in property prices (Murfin & Spiegel, 2020; Bernstein et al., 2019; Baldauf et al., 2020). Rather, there appear to be important heterogeneities based on the crystallisation of risk (Zhang, 2016), the salience of damage (Garnache & Guilfoos, 2019) and climate change beliefs (Bernstein et al., 2019) – rendering studies of lender reaction to climate change projections all the more important. Another related strand of research studies 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).

My dissertation is closely related to the literature on climate change and property prices because of the two-way relationship between house prices and lender behaviour: lender behaviour can also have an impact on house prices through the terms, conditions and the availability of real estate financing.

2.6. Lender heterogeneity

Fuster et al. (2019) show that in recent years the number and the 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, 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) points to less human involvement and less loan officer discretion. Unlike banks, non-banks are unable to (even partially) rely on deposits to fund their originations, thereby adopting an originate-to-securitize funding model (Gete & Reher, 2021), with the most notable form of securitisation being through GSEs. With the majority established in the past few years (Lux & Green, 2015), it may be reasonable to hypothesise that non-banks are more open to new datasets, such as those related to the changing climate.

3. DATA

Table 1 provides an overview of all the data used in the dissertation. The backbone of the dissertation relies on mortgage and climate data which is used in all three case studies.

Table 1 Sources of data

Type of data	Source	Case study
Climate change projections	ACIS	1,2,3
Mortgage data	HMDA	1,2,3
Regional land area	US Census Bureau	1
Regional population	US Census Bureau	1
Regional economic performance	Bureau of Economic Analysis	1
Regional Unemployment	US Bureau of Labor Statistics	2,3
Regional House Price	FHFA	2,3
FICO credit scores	Fannie Mae and Freddie Mac	2
Census tract to zip	US Department HUD	2
Climate opinion	Yale	2
List of banks and non-banks	Buchak et al. (2018)	2
Coastal counties	NOAA	2,3
Natural disasters	FEMA	2,3
Humidity data	NOAA	2,3
GSE limits	FHFA	3
Lender heterogeneity	CFPB	2,3
Flood insurance	NFIP	3
Housing units	US Census Bureau	3

For climate change projections I 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) and have first become available in the second half of 2016 (USGS, 2016). 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). In their overview of climate-economy literature and specifically on climate projection data, Dell et al. (2014) point to the UN's IPCC report as reference. 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. All this suggests that those lenders that do wish to take account of climate change in their lending decisions can easily access a widely-respected and quoted data source that reflects the synthesis of leading climate scientists' views. Unless indicated otherwise, I use the medium carbon emission scenario.

I apply thresholds that are also used by ACIS. Unless indicated otherwise I define:

- hot days as days during which maximum temperatures exceed 90°F,
- drought days as days during which precipitation is less than 0.01 inch,
- flood days as days during which precipitation exceeds 1 inch.

Per annum figures for these variables are available within projections and historical data.

For loan-level mortgage data I use the HMDA database of the Federal Financial Institutions Examination Council (FFIEC) which, for US mortgages, is the most comprehensive publicly available database. It was created by the US Congress decades ago to help track how well lenders are serving the housing needs of local residents, to uncover potential discrimination and to help allocate public investments across the country (FFIEC, 2021). It includes granular information on loan, borrower and property characteristics such as the the loan amount, the income, the race and the ethnicity of the borrower, the census tract of the property, and whether the loan was sold on within a year to GSEs. 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 (HAC, 2011). The dissertation looks at a subset of the mortgage market, those I label „vanilla mortgages": conventional loans, secured by 1st lien, single family (up to 4 units), not manufactured (site-built), for home purchase, loan originated. Keenan and Bradt (2020) also focus on such a subset, excluding from their sample multifamily condominiums, manufactured housing and refinanced loans to maximize homogeneity and on account of different risk profiles.

I turn to data from US authorities on county-level land area and population (US Census Bureau), regional economic performance (Bureau of Economic Analysis), the labour market, in particular county-level unemployment rate (US Bureau of Labor Statistics) and county-level house price indices (Federal Housing Finance Agency).

The US Census Bureau conducts a census every 10 years which is the most accurate source of data for the US population (US Census, 2023). The two most recent ones are from 2020 and 2010. Population estimates are provided in the years when a census does not take place. Responding to the census is compulsory. Amongst others, the data has an influence on the spatial distribution of federal funding and representation in the House of Representative and in state legislatures. The US Census Bureau also provides estimates for housing units at a county level.

The Bureau of Economic Analysis (BEA) – an agency under the Department of Commerce – provides data on the US economy including GDP, foreign trade and investment and industry (Bureau of Economic Analysis, 2024). Of particular use to this dissertation is the county-level GDP which includes contributions from 34 industries. The data is published annually since 2019.

The US Bureau of Labor Statistics publishes local area unemployment statistics including at a county level (US Bureau of Labor Statistics, 2023). These are estimates that rely on data from the Current Population Survey, a nationwide household survey, the Current Employment Statistics survey, state unemployment insurance systems and the Census Bureau's American Community Survey. The estimates are adjusted to sum to state-wide figures.

The Federal Housing Financing Agency's house price index (FHFA HPI) tracks changes in single-family house prices since 1975 (FHFA, 2024). It follows a weighted repeat-sales methodology which means that it observes the change in house prices on the same properties in repeat sales or refinancings from mortgage transactions where mortgages have been bought or securitised by either Fannie Mae or Freddie Mac, two government agencies. The data comprises tens of millions of sales which enables a granularity at the county and even census tract level.

I use Fannie Mae and Freddie Mac databases for credit scores. Importantly, HMDA data does not include credit scores. Fannie Mae and Freddie Mac are government-sponsored enterprises (GSEs) – created to support the housing market. They publish loan-level detail on a large subset of the loans they purchase and include FICO credit scores. The GSEs only cover a subset of the mortgage market as they can only purchase so-called conforming loans that are below the loan limit (USD 453 100 in 2018 for most of the US) and meet other criteria such as LTV, debt-to-income ratio and credit score requirements.

I use crosswalk files from the US Department of Housing and Development (HUD) to map census tracts to first-three-digit zips. Zip codes are postal codes used by the US postal service. Census tracts are the smallest territorial unit used for statistical purposes and Census Bureau also publishes data on this granular basis (US Census Bureau, 2015). Census tract population is about 4000. The mapping between census tracts and zip codes 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.

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

Coastal counties in the 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. I turn to NOAA Comparative Climatic Data for average historical afternoon humidity data. Humidity data is sourced from a central weather station for each state. I use this data only for a very high-level robustness test.

I use two sources to classify lenders into different categories. First, I turn to Buchak et al. (2018) who manually classify lenders into bank and shadow bank categories. Buchak et al. (2018)'s classification covers the largest lenders – defined as the top 50 originators within Fannie Mae, Freddie Mac and FHA data and other lenders from HMDA data so that their classified sample includes 80% of 2010 loan originations by value. The authors follow Financial Stability Board definitions for bank – "deposit-taking corporations" – and non-banks – "credit intermediation involving entities and activities outside of the regular banking system" (FSB 2015 p.1).

In other parts of the analysis I use CFPB (2020) lender categories which are defined as follows:

- "Small banks consist of those banks with assets (including the assets of all other banks in the same banking organization) of less than $1 billion at the end of 2016." (CFPB, 2020, p. 60)
- Large banks are banks that are not small banks.
- "Credit unions are non-profit financial cooperatives, meaning that these depository institutions are owned and operated entirely by their members." (CRS, 2022, p.1)
- Affiliated mortgage companies are non-depository mortgage companies owned by or affiliated with a banking organization or credit union (CFPB, 2020, p. 60)
- Independent mortgage companies are mortgage companies that do not fall into the category above.

I source flood insurance data from the government's National Flood Insurance Program (NFIP) which is behind the vast majority of flood insurance policies in the US (Kousky, 2018). The origin of the NFIP goes back to 1968 when Congress passed an act to reduce flood losses and provide flood insurance protection (FEMA, 2024). NFIP insurance can cover the building structure, and the content and personal property within the building. Not all properties and areas are eligible for NFIP insurance.

4. CASE STUDY 1: LOAN AMOUNTS, REJECTION RATES AND EXTREME HEAT

4.1. Overview of the case study

The case study looks at how much US mortgage lending goes to the areas that are most vulnerable to future heatwaves. I find that relative to their land share, proportionally more lending flows to the areas that are likely to be most exposed to heat in the future. This is likely because population and economic output are relatively higher in these areas. And while this would suggest that climate risk appears less of a factor in lending decisions, lenders do reject proportionately slightly more mortgage applications in the counties that are expected to be the hottest.

4.2. Research questions

In the case study, I would like to draw attention to the fact that spatial inequalities in lending can also be examined from a climate change perspective – potentially of use to decision-makers with a long term horizon. The analysis is mainly based on descriptive statistics – partly due to the nature of the research questions and partly to the lack of complete data – and lays the ground for further research that could, for example, explore the relationship between climate change and the denial of loan applications in more detail.

The research questions are as follows:

1. How does the volume of mortgages originated in the US counties that are most vulnerable to future heatwaves, compare to such counties' share of land area, economic importance and population?
    - Hypothesis: It appears that even in the case of a more salient type of risk (SLR), the housing market is yet to fully and universally incorporate climate risk (Murfin & Spiegel, 2020). What is more, even recent construction rates fail to reflect the degree of exposure (Climate Central, 2019). I, therefore, expect limited recognition in lenders' decisions on origination of a future increase in heatwaves brought on

by climate change. I expect lending volumes to be broadly in line with population and local economic activity.

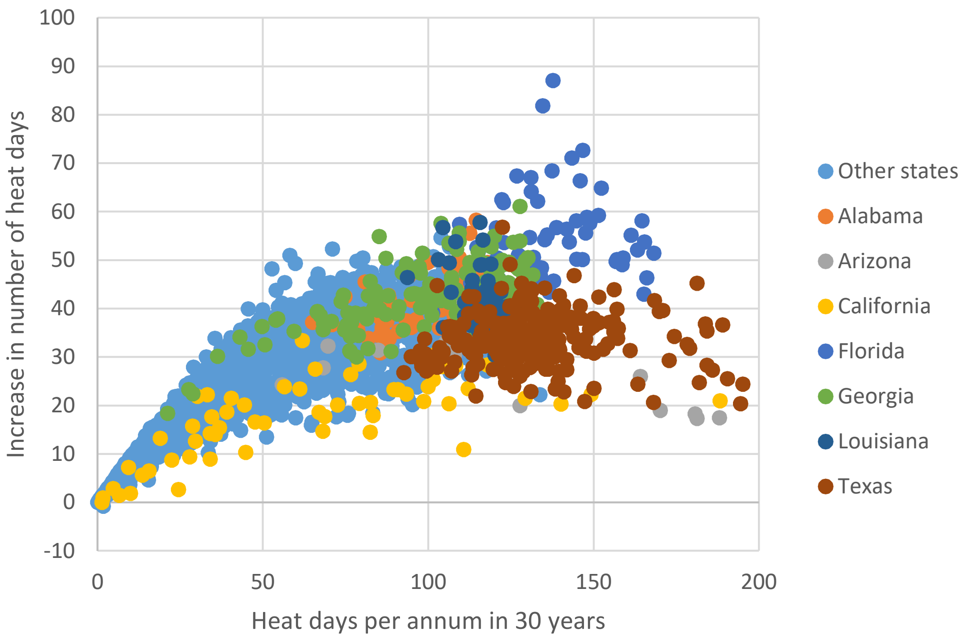
2. What do we know about supply and demand effects in lending patterns?
   - Hypothesis: I expect the demand for loans to broadly follow the spatial patterns of population and economic activity. As I do not expect much incorporation of future heatwave risk in lenders' decisions on whether to accept or reject a loan, I expect origination volumes to broadly reflect the spatial patterns in the demand for loans, especially once loan quality (or factors that can be associated with loan quality) has been controlled for.

4.3. Data and methodology

I turn to ACIS for climate data and HMDA for mortgage data. Land area and population data are from the US Census Bureau, and regional economic performance data are from the Bureau of Economic Analysis. The study is conducted at the county level by aggregating micro-level loan contract data. The study does not cover Alaska and the so-called US territories (islands that are not linked to the 50 US states). The data is discussed in more detail in Section 3.

Within climate change, I focus on the number of extremely hot days, when the daily maximum temperature exceeds 90°F, or 32.2°C. This cut-off value is also used in the ACIS database. I distinguish between future *levels* (the average of projections for 2041–2050) and the *change* compared to the most recent data (the difference between the average of 2041–2050 and the average of 2003–2012). Although the two heat variables are highly correlated, the highest increases in heat days are not always expected in the counties that are at the top of the heat list today. In some counties in California and Texas, for example, the projected increase is not outstanding, but they will nevertheless be among the hottest counties because they are already there (Figure 4). The number of heat days is forecast to increase most in the south-eastern part of the US (Florida, Georgia, Alabama, etc.).

Figure 4 Increase in the number of heat days and their future level



Note: Each dot represents a county. The Y-axis shows the future level of heat (>90°F) days (average of projections for 2041–2050), while the X-axis shows the projected change in the number of heat days (the difference between the averages of 2041–2050 and of 2003–2012). Colouring is by state. States that are most exposed to future heat (either by X or Y heat variables) are given separate colours, counties from other states are shown in light blue. Source: ACIS.

In the first part of the analysis, I compare the volume of originated loans and loan applications (flow) with population, GDP and land area data according to the area's exposure to heat (looking at both the level and the change). For lending data, I examine "vanilla" mortgages as detailed in Section 3.

In the second part of the analysis, loan denials rates are constructed. The simple denials rate is the ratio of denied loan applications to the sum of originated loans and denied loan applications. This is used, for example, by Duan and Li (2019). I calculate rates based on both the volume of (mortgage) lending (flow) and the number of loan applications. I then generate sophisticated denials rates based on Keys and Mulder (2020), with the aim of filtering out the effects of known characteristics of loan applications and lenders. The following equation is used for loan application *i*, in county *j* and year *t*:

$$
\begin{aligned}
Denial_{i,j,t} = {} & \alpha + \beta_{j,t}CountyYearDummy_{j,t} + \beta_1 Loan\ amount_i \\
& + \beta_2 Loan\ amount_i^2 + \beta_3 LTI_i + \beta_4 LTI_i^2 \\
& + \beta_5\left(CLL_{j,t} - Loan\ amount_i\right) + \beta_6\left(CLL_{j,t} - Loan\ amount_i\right)^2 \\
& + \beta_7 Ethnicity1_i \\
& + \beta_8 Ethnicity2_i + \beta_9 Ethnicity3_i + \beta_{10} Genderdummy1_i \\
& + \beta_{11} Genderdummy2_i + \beta_{12} Owneroccupied_i \\
& + \beta_{13} Local\ lender\ dummy_i + \epsilon_{i,j,t}
\end{aligned} \tag{1}
$$

Denial is a dummy variable with a value of 1 indicating denial of the application. CLL means the county and year-specific loan contract level cut-off value above which the GSEs will no longer purchase loans. LTI is the ratio of the loan amount to income. Demographic characteristics are also included: I take into account the ethnicity (White, Asian, Black, and Hispanic) and gender (male, female, or male and female combined) of the loan applicant. This is important because, although I do not have information on debtor classification or credit scores, it may correlate with certain characteristics, and skin colour, for example, may also play a role in the lender's decision – this is, in fact, partly the reason why the HMDA database was set up (FFIEC, 2021). Other control variables include the loan amount, the square of the loan amount and a dummy variable indicating whether the owner lives in the property. Finally, the literature suggests that lender behaviour may be affected by whether the lender is considered local, so I construct a dummy variable for this defining a lender as local in line with Keys and Mulder (2020) if it disburses at least 10 per cent of its annual lending in the county.

To construct the sophisticated denials index, $\beta_{j,t}$ values are added to the average denials rate calculated from the data so that the index values are between 0 and 1. Thus, the index is a measure of how application denials have evolved across counties and years, beyond the known loan-level characteristics. The statistical method for computing the index relies on having county no*year dummies. I use three years (2017-2019) as the basis for the index calculation because more than 10,000 explanatory variables presents computing challenges. I do not have this constraint when computing simple denials rates.
The key variables are summarised in *Table 2*.

Table 2 Case study 1 Main variables

Variable	Observations	Average	Standard deviation	P1	P25	Median	P75	P99
Number of heat days in 30 years	3,067	67.07	39.44	2.34	35.23	62.67	98.19	163.23
Increase in the number of heat days	3,067	29.9	11.83	1.59	21.98	31.91	38.03	55.51
Lending vs. territorial share	3,067	0	0.16	–0.2	–0.03	–0.02	–0.01	0.52
Simple denials rate (sum)	28,808	0.15	0.08	0.02	0.09	0.13	0.18	0.45
Sophisticated denials index	9,197	0.18	0.07	0.03	0.14	0.17	0.2	0.45

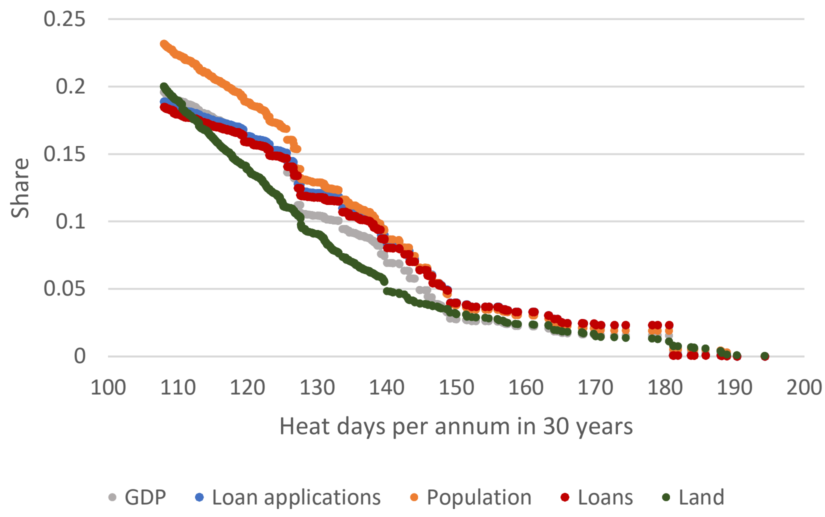
Note: The simple denials rate is for the years 2010–2019, while the sophisticated denials index is for the years 2017–2019. Source: ACIS, HMDA, author calculations.

4.4. Results and discussion

4.4.1. Volume of (mortgage) lending and loan applications

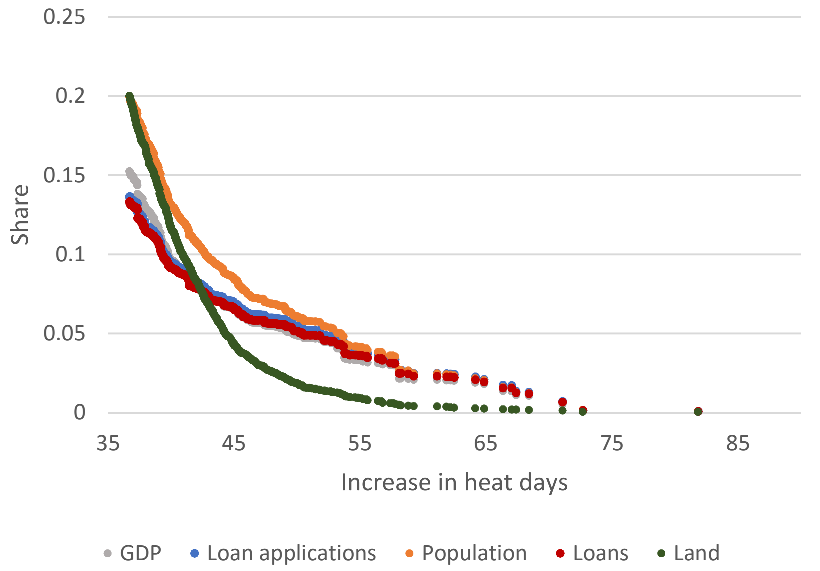
The spatial distribution of the population and the country's economic performance is uneven. 13 per cent of the US population, 11 per cent of economic output and nearly 12 per cent of mortgage lending is tied to the areas expected to be amongst the hottest 10 per cent in 30 years (Figure 5). Similarly, areas that are expected to experience at least 140 heat days in the future – i.e. the hottest 5 per cent of counties in the future based on land area – account for 7 per cent of total economic GDP and 8–9 per cent of population and originated loans (Figure 5). Focusing on the change in heat days over the next three decades, rather than the level of future heat, gives a similar picture. The 5 per cent of the country's area with the highest projected increase in heat days covers 9 per cent of the country's population, 7 per cent of originated loans and 7 per cent of GDP (Figure 6).

Figure 5 Mortgage lending in the area as a function of the number of "hot" days expected in 30 years – extremes



Note: The figure shows the share of the country's originated loans, population, GDP, loan applications and land area in 2019 that were in counties where x or more heat days (>90°F) are expected in 30 years (average of 2041–2050). Source: ACIS, HMDA, US Census Bureau, BEA

Figure 6 Mortgage lending as a function of the expected warming of the area – extremes



Note: The figure shows the share of the country's originated loans, population, GDP, loan applications and land area accounted for by counties with x or more increase in the number of heat days (> 90°F) over the next 30 years (average of 2041–2050 minus the most recent historical data: average of 2003–2012). Source: ACIS, HMDA, US Census Bureau, BEA

Next, I examine whether the pattern is driven by a few (large) counties, or the statement is true for a wide range of counties. To answer this question, I first compare the land share of a county with its share in lending (Table 3, variable E). Table 3 shows the counties with the largest difference in either direction. In particular, California's affluent regions benefit from a higher volume of lending relative to their land share, with the sparsely populated western US counties at the bottom of the list.

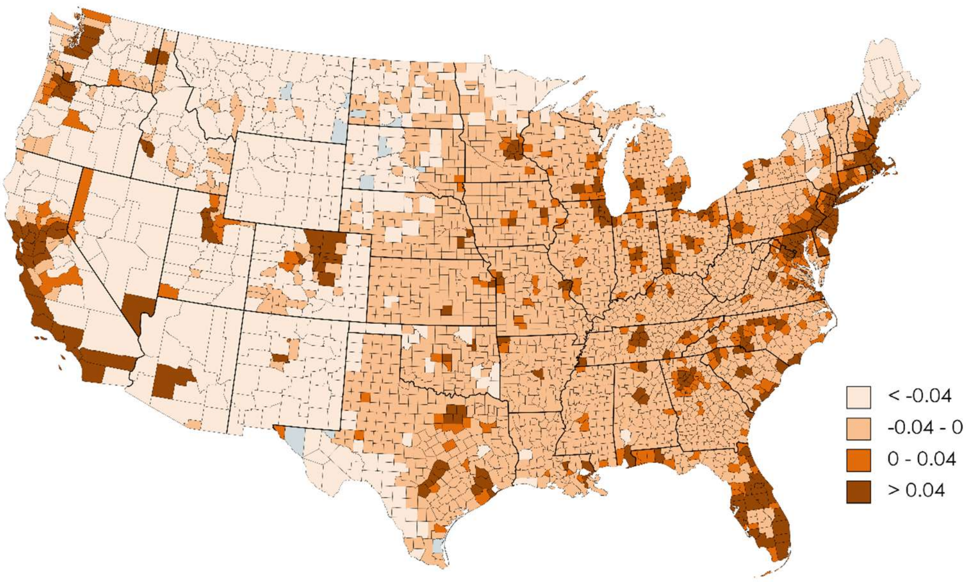
Table 3 Where does loan share differ most from land share?

County	**Share of county (per cent)**				**Lending % – Area %**	**Population % – Area %**	**GDP % – Area %**
	Lending	**Land area**	**Population**	**GDP**			
	A	B	C	D	**E = A – B**	F = C – B	G = D – B
Highest volume of lending relative to share of land area							
Los Angeles County, CA	4.95	0.14	3.08	3.87	**4.81**	2.94	3.73
Orange County, CA	2.36	0.03	0.97	1.27	**2.33**	0.95	1.25
Santa Clara County, CA	2.04	0.04	0.59	1.57	**2.00**	0.55	1.52
Maricopa County, AZ	2.24	0.31	1.38	1.25	**1.92**	1.06	0.93
San Diego County, CA	1.99	0.14	1.02	1.20	**1.84**	0.88	1.05
Lowest volume of lending relative to share of land area							
Humboldt County, NV	0.00	0.38	0.02	0.01	**–0.38**	–0.36	–0.37
Malheur County, OR	0.06	0.45	0.07	0.03	**–0.40**	–0.39	–0.43
Inyo County, CA	0.01	0.59	0.02	0.01	**–0.58**	–0.57	–0.57
Harney County, OR	0.06	0.63	0.04	0.04	**–0.58**	–0.59	–0.60
Sweetwater County, WY	0.01	0.62	0.01	0.01	**–0.61**	–0.61	–0.61

Note: In line with the focus of the study, the calculations exclude Alaska and the islands not connected to the US (Territories of the United States) as well as 12 additional counties due to data limitations. CA: California, NV: Nevada, OR: Oregon, WY: Wyoming. Source: ACIS, HMDA, US Census Bureau, BEA

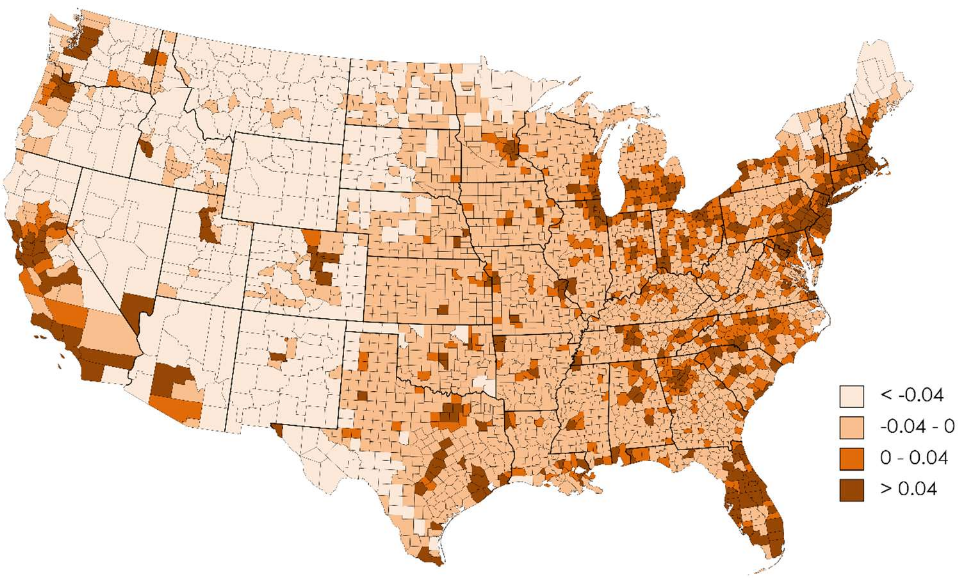
The difference between lending and loan shares (variable E in Table 3) is also depicted on a map (Figure 7). We can see that, in addition to some counties in California, there is more lending in the northeast coastal region, Florida and around some large cities, relative to their area. It is also striking that this value is generally lower in the western half of the country. A similar pattern can be recognised when comparing loan share with the share of population (Figure 8; this is variable F in Table 3) and the share of economic output (not shown separately, variable G in Table 3). The relationship will be explored more formally below.

Figure 7 Relationship between land share and loan share



Note: The variable is the difference between the county's share of lending (A: amount of loans disbursed in the county / national volume of lending) and its geographical importance (B: land area of the county / land area of the country), multiplied by 100. Index = (A–B)*100. There are more than 3,000 counties.
Source: HMDA

Figure 8 Relationship between land share and population



Note: The variable is the difference between the proportion of inhabitants in the county (A: population of the county / population of the country) and its geographical importance (B: land area of the county / land area of the country), multiplied by 100. Index = (A–B)*100. There are more than 3,000 counties.
Source: HMDA

On average, the loan share of counties exposed to heat days is higher than that of less exposed counties (Table 4, examining variable E above). However, the difference is statistically significant largely only for heat variable 2 – the increase in the number of heat days. This is primarily due to much lending activity in the south-eastern part of the country, particularly in several counties in Florida, where a significant increase in the number of heat days is expected. By contrast, some areas that are already hot (and will be among the hottest in 30 years), such as several counties in Arizona, have relatively little lending activity. Table 4 shows, for example, that counties where the number of heat days is forecast to rise by at least 50 days have an average difference of 0.042 percentage points between their lending share and their land share; whereas in other counties it is approximately 0 (Test 5). The difference is not insignificant in economic terms either, since the average share of a county (in both lending and land area) is 0.03 percentage points (1/3,067 *100) in the 3,067 counties in the case study, and such a difference between the counties' loan share and land share is not typical (in absolute value, the difference is less than 0.04 percentage points in 79 per cent of the counties and less than 0.03 percentage points in 69 per cent of the counties).

Table 4 Loan share by heat days

Number of heat days in 30 years					
Test	Group	Observations	Average	St. error	Prob (T<t)
1. >=130	0	2,871	–0.001	0.003	
	1	196	0.014	0.013	
	Diff (0–1)	3,067	–0.015	0.013	0.135
2. >=140	0	2,982	–0.001	0.003	
	1	85	0.037	0.028	
	Diff (0–1)	3,067	**–0.038***	0.028	0.088
3. >=150	0	3,015	–0.000	0.003	
	1	52	0.015	0.039	
	Diff (0–1)	3,067	–0.015	0.039	0.348
Increase in the number of heat days					
Test	Group	Observations	Average	St. error	Prob (T<t)
4. >=45 days	0	2,868	–0.001	0.003	
	1	199	0.012	0.006	
	Diff (0–1)	3,067	**–0.012*****	0.006	0.032
5. >=50 days	0	2,989	–0.001	0.003	
	1	78	0.042	0.014	
	Diff (0–1)	3,067	**–0.043*****	0.014	0.002
6. >=55 days	0	3,034	–0.001	0.003	
	1	33	0.082	0.028	
	Diff (0–1)	3,067	**–0.083*****	0.028	0.003

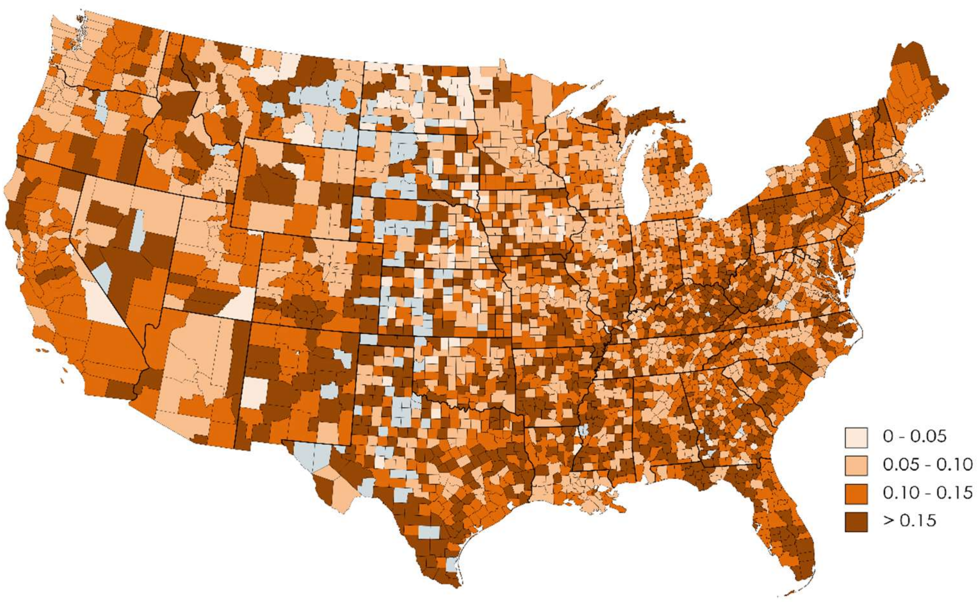
Note: 2-sample t-test assuming different standard deviations. The examined variable is the difference between the role of the county in lending (A: volume of loans disbursed in the county / volume of loans disbursed in the country) and its geographical importance (B: geographical extent of the county / geographical extent of the country), multiplied by 100. Variable = (A–B)*100. Group 1 indicates the counties exposed to extreme heat based on the number of future heat days (cut-off values for Tests 1, 2 and 3: 130, 140 and 150 heat days, respectively), or based on the expected increase in the number of heat days (cut-off values for Tests 4, 5 and 6: +45, +50 and +55 heat days, respectively). Prob (T<t) indicates the significance level at which we can reject the null hypothesis that the mean value is the same in the two groups and accept the alternative hypothesis that the mean value of group 1 is greater than that of group 0. Statistically significant differences are marked also with asterisks: * significant at 10%, ** significant at 5%, *** significant at 1%. Source: ACIS, HMDA

The spatial distribution of loan applications is very similar to that of loans (see Figure 5 and 6): thus, in the areas most exposed to climate change the share of loan applications exceeds the land share of these counties, but is not out of line with the share of economic activity or population. In other words, the expectation of how much a given area will change in the future in terms of liveability does not seem to play a significant role in lending activity, either on the supply or on the demand side. I now proceed to conduct a more formal analysis regarding the behaviour of lenders.

4.4.2. Simple denials rate

I examine whether the relatively high volume of lending flowing to the counties most exposed to heat risk may be driven by lower denials rate by lenders. Conversely, the opposite could suggest that although banks have a reduced preference to lend in these areas due to future risks, high demand pressures still result in significant lending. I first look at simple denials rates. Simple denials rates tend to be low (or absent) in the northern-central part of the country; these are areas less exposed to future heat (Figure 9). Many southern counties (Florida, Texas, some counties in New Mexico) have higher denials rates.

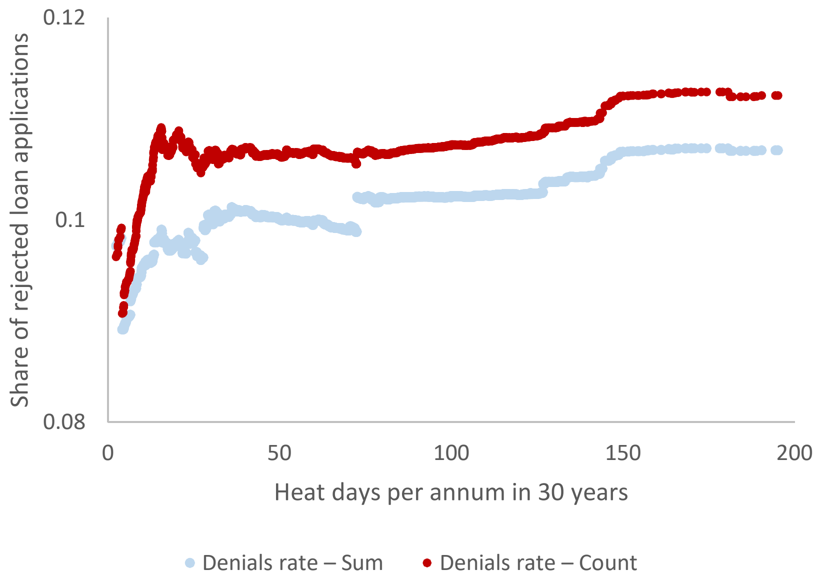
Figure 9 Simple denials rate



Note: The simple denials rate is the ratio of denied loan applications to the sum of disbursed loans and denied loan applications. No rate is calculated for fewer than 10 loan contracts. The maps shows data from 2019 and includes more than 5 million loan applications. Source: HMDA 2019, mapchart.net.

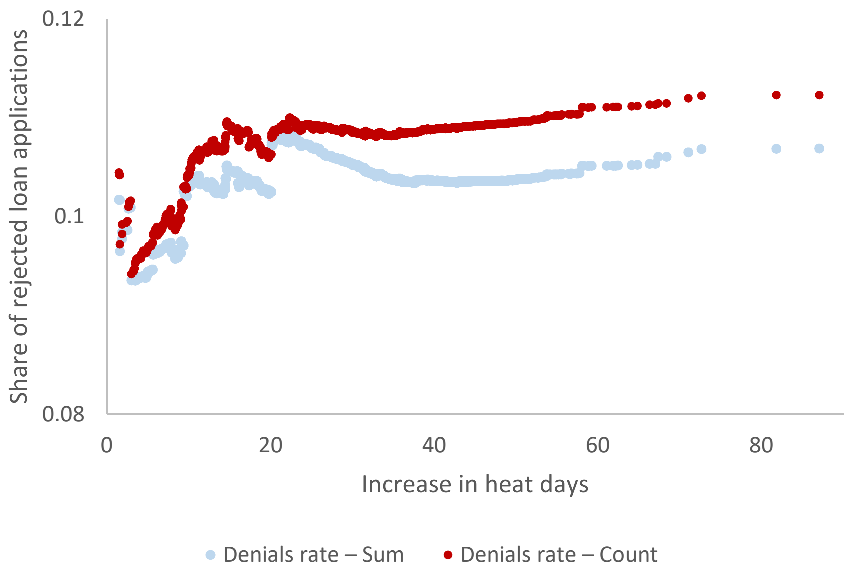
This would suggest that lenders' willingness to lend is slightly lower in places most exposed to climate change. More loan applications are denied in areas where, for example, more than 150 days of heat are expected in 30 years (Figure 10). Figure 11 shows that in areas where the number of heat days is expected to increase only minimally, fewer loan applications are denied than in counties more exposed to climate change. In the northern counties in general, somewhat fewer loan applications are denied, which is reflected, among other things, in the low values of the X-axis in Figures 10 and 11. And at the high values of the heat variables, the southern counties with the highest denials rate and the highest exposure to heat appear in the cumulative denials rate. There may be reasons independent of climate change behind the pattern, but it is also possible that the future macroeconomic expectations used in the lender's decisions reflect climate change to some extent. Figures 10 and 11 use lending data for 2019 and reflect over 5 million loan applications. In general, though not always, a similar pattern characterises the various years in the past decade.

Figure 10 Cumulative denials rate as a function of the expected number of heat days in the area in 30 years



Note: The figure shows the proportion of loan applications that were denied by the lenders, based on the number of loan applications or the amount of loan applied for. For a given x, I calculate with the population of loan applications where at the location of the real estate (county) x or fewer heat days (>90°F) are expected in 30 years (average of 2041–2050). The figure reflects a total of more than 5 million loan applications, and the cumulative denials rates are shown from a minimum population of 50,000 loan applications. Lending data: 2019. Source: ACIS, HMDA.

Figure 11 Cumulative denials rate as a function of the expected warming of the area



Note: The figure shows the proportion of loan applications that were denied by the lenders, based on the number of loan applications or the amount of loan applied for. For a given x, I calculate with the population of loan applications where at the location of the real estate (county) the increase in the number of heat days (> 90°F) is x or fewer over the next 30 years (average of 2041–2050 minus the most recent historical data: the average of 2003–2012). The figure reflects a total of more than 5 million loan applications, and the cumulative denials rates are shown from a minimum population of 50,000 loan applications. Lending data: 2019. Source: ACIS, HMDA.

4.4.3. Sophisticated denials index

The loan denial pattern in Figure 10 and 11 does not necessarily reflect the willingness of lenders to lend, as there may be regional differences in the characteristics of loan applications. It is possible, for example, that in some areas loan applications have a higher risk and therefore there is a higher rate of denials, with unchanged willingness to lend. Spatial differences in the risk of loan applications may be the result of climate change-related or non-climate change-related causes. An example of the former is when wealthy people with good credit ratings move away from areas most vulnerable to climate change.

In the sophisticated denials index, I try to filter out the available loan application parameters, such as the demographic characteristics of the borrower or the size of the loan relative to income. Thus, using equation (1), I construct a county-level index and then examine the spatial distribution of the index values. Statistical tests continue to show that, on average, slightly more loan applications are denied in the counties most exposed to temperature change (looking at both future levels and changes) (Table 5). In areas where at least 150 heat days are expected in 30 years, the average value of the index is 0.23, which is 5 percentage points higher than the average for the rest of the country (Table 5, Test 3), and in the areas where the projected increase in the number of heat days is at least 50 days, the average value of the sophisticated denials index of 0.2 is 0.02 higher than the average of areas where the increase in heatwaves is expected to be lower (Table 5, Test 5). Even after applying different cut-off values for extreme heat (level and change), in all cases examined there is a statistically significant difference between the average index values of the extreme and that of the less exposed areas (Table 5, tests 1–6). It can be considered significant also in an economic sense if out of every 100 dollars of loan applications 2 to 5 dollars more are denied in the areas that are most exposed to future heat.

Table 5 Sophisticated denials index based on climate exposure

Number of heat days in 30 years					
Test	Group	Observations	Average	St. error	Prob (T<t)
1. >=130	0	8,621	0.178	0.001	
	1	576	0.210	0.004	
	Diff (0–1)	9,197	**–0.032*****	0.004	0.000
2. >=140	0	8,945	0.179	0.001	
	1	252	0.223	0.006	
	Diff (0–1)	9,197	**–0.044*****	0.006	0.000
3. >=150	0	9,043	0.179	0.001	
	1	154	0.232	0.009	
	Diff (0–1)	9,197	**–0.053*****	0.009	0.000
Increase in the number of heat days					
Test	Group	Observations	Average	St. error	Prob (T<t)
4. >=45 days	0	8,610	0.179	0.001	
	1	587	0.197	0.003	
	Diff (0–1)	9,197	**–0.019*****	0.003	0.000
5. >=50 days	0	8,966	0.179	0.001	
	1	231	0.203	0.004	
	Diff (0–1)	9,197	**–0.024*****	0.004	0.000
6. >=55 days	0	9,098	0.180	0.001	
	1	99	0.201	0.005	
	Diff (0–1)	9,197	**–0.022*****	0.005	0.000

Note: 2-sample t-test assuming different standard deviations. The examined variable is the sophisticated denials index. Group 1 indicates the counties exposed to extreme heat based on the number of future heat days (Tests 1, 2 and 3: from 130, 140 and 150 heat days, respectively) or based on the expected increase in the number of heat days (Tests 4, 5 and 6: from +45, +50 and +55 heat days, respectively). Prob (T<t) indicates the significance level at which I can reject the null hypothesis that the mean value is the same in the two groups and accept the alternative hypothesis that the mean value of group 1 is greater than that of group 0. Statistically significant differences are also marked with an asterisk: significant at *** 1 per cent. Source: ACIS, HMDA.

4.5. Conclusions from the case study

High temperatures have well-documented negative effects on the human body, productivity and the economy. The most effective protection against heat available on a large scale today – air conditioning – is environmentally unsustainable. Therefore, it matters where and with what technology buildings and neighbourhoods that will face the future climate are built today. In this case study, I used the example of US mortgage lending to examine whether more mortgages are originated in counties that are most vulnerable to future heatwaves, relative to their land area, economic importance and population. My conclusion is that the mortgage share of these areas is higher than their land share, and this appears to be linked to their greater economic activity and higher population. In fact, lenders deny slightly more loan applications in these areas, which appears to suggest that that it is not a greater lending appetite that is behind the higher lending volumes in heat-prone areas. Similar analyses for other countries or climate change dimensions can enrich our knowledge on the relationship between mortgage lending and climate change.

5. CASE STUDY 2: INTEREST RATES AND EXTREME HEAT

5.1. Overview of the case study

For the contiguous US states I 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.

5.2. Research questions

1. Are interest rates higher and loan terms shorter in areas that are more exposed to climate change, controlling for other variables?
    - Hypothesis: Based on the literature (see Section 2.4. and 2.5.), I expect limited recognition, in lenders' rate-setting or loan terms, of a future increase in heatwaves brought on by climate change. This is because even in the case of a much more salient climate risk (SLR), there is debate amongst scholars whether there is, in fact, price incorporation (e.g. Murfin & Spiegel, 2020).
2. Do we see additional concerns reflected in mortgage characteristics at the extremes of projected levels of hot days?
    - Hypothesis: There is limited evidence from the literature on widespread and universal pricing in of climate concerns (e.g. Murfin & Spiegel, 2020). But one study that does find price incorporation (Bernstein et al., 2019) documents non-linearities: a much higher discount for properties exposed to a lower level of SLR (1-3 feet SLR associated with a 14-15% discount) than properties exposed to higher levels of SLR (5 feet SLR associated with a 4% discount). Therefore, although overall I expect limited pricing in of future heatwave risk, I expect some incorporation of the risk at the extremes.
3. Do climate change concerns appear more pronounced in the mortgage rates of certain lenders?

- Hypothesis: As mentioned in the previous hypotheses, I do not expect much pricing in overall. I do, however, expect some pricing in from the most forward-looking and agile lenders. One may argue, that some non-bank lenders may be in this group as most of them have been established in the past few years and may be seen as more open to new types of data (Section 2.6.).

5.3. Data and methodology

A general discussion of Climate and mortgage data is included in Section 3. For this case study I 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. I include loans with the following characteristics: 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. In other words, I seek to keep the most standard type of mortgages similar to Keenan and Bradt (2020). I drop around 7,500 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 (HAC, 2011).

I include a number of controls. Unemployment rate by county is sourced from the US Bureau of Labor Statistics. I calculate county-level house price volatility metrics from Federal Housing Finance Agency (FHFA) House price indices.

For credit scores I use Fannie Mae and Freddie Mac databases. These two government-sponsored enterprises (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) and meet other criteria such as LTV, debt-to-income ratio and credit score requirements.

I 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.

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

Coastal counties in the 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. I turn to NOAA Comparative Climatic Data for average historical afternoon humidity data.

Table 6 provides an overview of the samples used in the study.

Table 6 Summary statistics for Case study 2 baseline sample

Panel A: Summary statistics for the baseline sample

	Level	N	Mean	Std. Dev.	1st Perc.	p25	Median	p75	99th Perc.
Diff2048_RCP4.5_90F	county	3109	32.21	12.3	1.87	24.53	34.02	40.43	59.04
Diff2048_RCP8.5_90F	county	3109	38.18	14.08	3.13	29.36	40.63	48.1	68.49
Diff2038_RCP4.5_90F	county	3109	28.42	10.93	1.13	21.6	30.39	36.15	50.6
Diff2038_RCP4.5_90F	county	3109	22.12	9.88	.66	15	23.55	29.19	43.15
Diff2048_RCP4.5_95F	county	3109	21.8	12.49	.28	12.34	21.13	31.14	50.04
Level2048_RCP4.5_90F	county	3109	69.31	39.13	2.6	38.88	64.79	100.44	164.76
Level2048_RCP8.5_90F	county	3109	75.28	40.01	3.62	43.3	72.79	107.84	172.23
Climate change belief (%)	county	3108	63.9	5.81	52.96	59.65	62.89	67.24	79.35
Rate spread (bps)	loan	2355080	46.51	56.61	-54.19	12.8	37	69.4	231.2
Combined LTV (%)	loan	2367233	82.16	15.21	29.41	79.86	80	95	101.78
Loan amount (‘000 USD)	loan	2485080	292.85	231.28	45	155	235	355	1195
Loan term (mths)	loan	2394751	346.71	46.54	180	360	360	360	360
Unemployment (%)	county	3108	4.09	1.4	1.9	3.1	3.9	4.8	8.4
Avg wkly wage (USD)	county	3108	794.14	181.97	527	684	759	854	1452
House price volatility	county	2403	34.14	22.01	9.36	19.56	27.1	41.78	110.28
Local competition	county	3086	75.32	17.65	39.08	61.45	75.27	90.88	100
Geographical concentration (5 states)	lender	4996	97.73	7.96	54.01	100	100	100	100
Geographical concentration (3 states)	lender	4996	96.02	11.26	40.30	99.14	100	100	100

Panel B: Summary statistics for the baseline sample

		Level	Proportion
Secondary residence (%)		loan	6.54
Applicant older than 62y (%)		loan	10.99
Ethnicity: Latino (%)		loan	8.56
Coastal (%)		county	10.47
Mortgage sold on within calendar year (%):		loan	
	No		23.24
	GSE		44.17
	Private securitizer		1
	Non-affiliated		30.1
	Affiliated		1.43
Debt-to-income ratio (%):		loan	
	<20%		6.44
	20-30%		20.37
	30-35%		18.97
	36-40%		19.03
	41-44%		16.92
	45-49%		17.08
	50-60%		0.87
	>60%		0.31
Race of applicant (%):		loan	
	White*		86.43
	Black**		4.98
	Asian		8.59
Sex of applicant (%):		loan	
	Male		33.41
	Female		22.98
	Joint		43.60

Notes: White* includes joint and unknown. Black** includes American Indian and 2 or more minorities. Climate variables measure: the projected rise in the number of days relative to the 2003-2012 average (Diff), or the projected number of days (Level) in which maximum temperatures exceed 90°F or 95°F. RCP 4.5 (RCP 8.5) indicates the medium (high) emission scenario. Summary statistics are calculated at a county (lender) level for county-level (lender-level) variables.

I use the following linear regression equation with OLS estimation for the rate spread baseline specification for approved loan i by lender l in county j:

$$\begin{aligned} Rate\ spread_{ijl} &= \alpha + \beta_0 Climate\ variable1_j + \beta_1 Climate\ variable2_j \\ &+ Controls_{ijl}^T \gamma + \epsilon_{ijl} \end{aligned} \tag{2}$$

Where Controls is a kx1 vector with k>1, γ is a kx1 vector of constants, and k denotes the number of control variables in the equation. 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 per cent 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 my study (therefore I don't include a simple level variable). I include Climate variable2 because temperatures have been shown to have non-linear effects at the extremes (e.g. Deschenes & 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. I 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. I apply heteroskedasticity-consistent standard errors clustered at a county level and I include a dummy for each lender. I acknowledge that some selection bias may arise if lenders reject more applications in areas more exposed to increased future heat. This bias would, however, be negative and the coefficient of the climate variable would be even greater absent such bias (Section 5.4.4.).

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

To study heterogeneity, I examine whether non-banks' rate-setting differs from that of banks. I use interaction terms between the climate variables and the non-bank dummy. In these specifications I omit the individual lender dummies as they would cause multicollinearity issues. Instead, I 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. I 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 Equation (2).

Although cross-sectional linear 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 downpayments from riskier borrowers in addition to setting higher interest rates. This may cause bias in my estimated coefficients. Therefore, as a robustness check, I follow the IV/2SLS approach as applied by Ambrose et al. (2018).

5.4. Results and discussion

5.4.1. Baseline results

Table 7 specifications 1-3 present regression results from Equation (2) without the second climate variable. 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 days' 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 the sample of 47bps. On a mortgage of $100,000 the additional cost on a mortgage from an area with the average projected increase in hot days compared to that from an area with no projected increase in hot days amounts to $20 each year (100,000*0.02%). 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 0.06-0.1bps (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 Equation (2) 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 7 Baseline regression results of climate projections on the rate spread

	(1)	(2)	(3)	(4)
Diff2048_RCP4.5_90F (days)	.0578**			.0722***
	(.0287)			(.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			
Observations	1994036	1994036	1994036	1994036
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. Heteroskedasticity-consistent standard errors in parentheses are clustered at county-level. *** p<.01, ** p<.05, * p<.1.

Table 8 presents probit regression results of climate projections on the probability that the term of the mortgage is shorter than the standard 30 years. 8% of the sample have a contractual maturity shorter than 30 years. The first climate variable's positive 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 an increase in the climate variable from the bottom to the top of the interquartile range, ceteris paribus, raises the probability of a sub-standard loan term by 1 percentage point. Projections of an extreme number of hot days increases the probability of a sub-standard term loan by 2 percentage points, assuming all variables are at their means. The coefficient of this second climate variable is also highly statistically significant. Directionally linear regressions with OLS estimation yield similar results.

Table 8 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		1981643				
McFadden's Pseudo R2		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 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, 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. Heteroskedasticity-consistent standard errors in parentheses are clustered at county-level. *** p<.01, ** p<.05, * p<.1. Dydx for factor levels is the discrete change from the base level.

5.4.2. Banks and Non-banks

Next, I 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, 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. I use Buchak et al. (2018)'s classification list of the largest bank and non-bank lenders. This covers 45% (40%) of the loans in my HMDA sample by value (number). The authors define banks as depository institutions. For the purposes of gauging the openness to new data sources, I argue 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 the purposes of this case study, 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-minutes or less is needed for signing – which is irrelevant for my purposes.

Non-banks, in general, apply lower interest rates in my sample than banks (Table 9). In areas where there is no projected increase in hot days, non-bank rate spreads are 10bps lower than bank spreads. This corresponds to $100 annually on a $100,000 mortgage. Non-banks rate spreads, however, are sensitive to the projected increase in hot days. In areas where the average of 32 days' rise in hot days is projected, interest rates on non-bank loans are only 5.5bps lower (-10+0.14*32) than those on banks. This equates to $55 annually on a $100,000 mortgage. The difference shrinks to only 2bps in areas where 59 days' rise in hot days is projected (which corresponds to the 99th percentile of hot day loan projections). Moreover, extreme hot temperature projections, as measured by the number of hot days in the future, increase rates on non-banks' lending by 10bps more than on banks' loans.

Table 9 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	837560		
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 per cent of counties and equivalent to at least 165 days with maximum temperatures above 90°F. I use Buchak et al. (2018)'s classification list of the largest bank and non-bank lenders. This covers 45% (40%) of the loans in my 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. Heteroskedasticity-consistent standard errors in parentheses are clustered at county-level. *** p<.01, ** p<.05, * p<.1.

I reach similar conclusions if I distinguish between independent mortgage companies, big and small banks, credit unions and affiliated mortgage companies following CFPB (2019). Only independent mortgage companies' interaction term with the climate variable is positive and statistically significant (untabulated).

5.4.3. Robustness checks

Some scholars have noted that loan interest rates and loan characteristics such as LTV or maturity are determined endogenously (e.g. Donaldson & Wetzel, 2018), raising questions about the bias of coefficients gained through linear regression OLS estimation method. To respond to such concerns, similarly to Ambrose et al., (2018), I use IV/2SLS. Following the logic of Ambrose et al. (2018), I 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.

I 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 10). 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-estimated linear regression results (coefficient of 0.06 in Table 7). 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 9.

Table 10 2SLS: Impact of climate projections on the rate spread

	(1) HMDA 2sls	(2) HMDA 2sls nonbank	(3) FFmatch1 2sls	(4) FFmatch2 2sls
Diff2048_RCP4.5_90F	.1611***	.1967***	.312***	.3708***
	(.0305)	(.0396)	(.085)	(.101)
Diff2048_RCP4.5_90F* Non-bank		.0781***		
		(.0302)		
Extreme no of hot days dummy	11.6808***	8.7413***	14.7618***	18.2167***
	(3.7452)	(1.9874)	(4.1741)	(4.9077)
Extreme no of hot days* Non-bank		10.8754***		
		(2.2838)		
Non-bank		-9.3325***		
		(1.143)		
FICO score			-.0153**	-.0137*
			(.007)	(.0074)
Lender rate spread	.9026***	.8472***	.5514***	.5599***
	(.0083)	(.0245)	(.0321)	(.0388)
Controls	Yes, see notes			
Observations	1993944	837560	27694	23314
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 per cent of counties and equivalent to at least 165 days with maximum temperatures above 90°F. Specification 2 (3) also include interaction terms between the climate variables and lenders' geographical concentration (a non-bank dummy). Specification 1 is run on the baseline dataset, specification 2 encompasses identified banks and non-bank firms only based on Buchak et al. (2018)'s classification list of the largest lenders. In order to include the FICO score, specifications 3 and 4 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 3) or the related observation is dropped (specification 4). 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. Heteroskedasticity-consistent standard errors in parentheses are clustered at county-level. *** p<.01, ** p<.05, * p<.1.

I also examine whether it is climate change beliefs rather than climate change projections that drive my 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. I 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 the 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 my 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 my analysis, I 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. I 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. I 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 I link these tracts to the first-three-digit zips accounting for the greatest proportion of the census tract's residential addresses. In specification 2 I drop observations from these tracts. I create two sub-samples from HMDA data: loans indicated as sold to Fannie and loans indicated as sold to Freddie. From these, as well as the Fannie and Freddie datasets, I first drop observations where my matching criteria would not uniquely identify a loan – resulting in dropping 25%, 23%, 4% and 4% of observations from the four datasets, respectively. I 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 my criteria. Matched Fannie and Freddie data are then combined. A comparison of the matched dataset with the original HMDA filtered dataset is presented in Table 11.

Table 11 Summary statistics for three datasets

Panel A: Summary statistics

	HMDA		**FF match 1**		**FF match 2**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Diff2048_RCP4.5_90F	29.54	14.48	27.82	13.4	27.78	13.6
Rate spread (bps)	46.51	56.61	47.02	43.62	47.5	43.74
Combined LTV (%)	82.16	15.21	78.06	18.8	78.14	18.78
Loan amount ('000 USD)	292.85	231.28	223.07	121.83	224.06	122.77
Loan term (mths)	346.71	46.54	338.1	57.94	338.54	57.43
Unemployment (%)	3.76	.98	3.89	1.08	3.9	1.09
Avg wkly wage (USD)	1038.94	272.56	981.39	223.58	985.93	224.77
Local house price volatility	51.8	30.52	47.22	29.19	48.68	29.75
Local competition	53.4	12.61	56.94	13.41	56.6	13.27
No of observations	2485080		32605		27416	

Panel B: Summary statistics

		HMDA	**FF match 1**	**FF match 2**
		Proportion	Proportion	Proportion
Secondary residence (%)		6.54	5.68	5.58
Applicant older than 62y (%)		10.99	12.04	12.09
Ethnicity: Latino (%)		8.56	7.64	8.11
Mortgage sold on within calendar year (%):				
	No	23.24		
	GSE	44.17	100	100
	Private securitizer	1		
	Non-affiliated	30.1		
	Affiliated	1.43		
Debt-to-income ratio (%):				
	<20%	6.44	9.63	9.66
	20-30%	20.37	24.38	24.04
	30-35%	18.97	20.51	20.3
	36-40%	19.03	14.88	14.98
	41-44%	16.92	13.26	13.46
	45-49%	17.08	16.38	16.58
	50-60%	0.87	0.97	0.98
	>60%	0.31	0	0
Race of applicant (%):				
	White*	86.43	91.37	91.07
	Black**	4.98	3.45	3.66
	Asian	8.59	5.18	5.27
Sex of applicant (%):				
	Male	33.41	32.14	32.47
	Female	22.98	22.79	23.32
	Joint	43.60	45.07	44.21

Notes: Detailed HMDA sample statistics are presented in Supplementary Table 1. FF match 1 indicates the dataset gained by matching Freddie and Fannie data with HMDA data based on purchaser, first-three-digit zip code, loan amount, debt-to-income ratio, interest rate on loan (to three decimal places) and the loan term. Only perfect matches are included. HMDA data is on a census tract (not zip) basis. Census tracts are mapped to first-three-digit zips using HUD crosswalk files. 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 (FF match 1) or related observation are dropped (FF match 2). The two climate 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 per cent of counties and equivalent to at least 165 days with maximum temperatures above 90°F. White includes joint and unknown. Black includes American Indian and 2 or more minorities. Summary statistics are calculated at a loan level unlike in Table 1 where county-level statistics are presented at a county level.

Table 10 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 my 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 my results, I remove loan contracts pertaining to the 10 or 20 percent of counties that experienced the most and/or least number of hot days from my sample and rerun the baseline regression (Table 12 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 heatwaves on mortgage rate spreads appears more significant – both statistically and economically – if I 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.

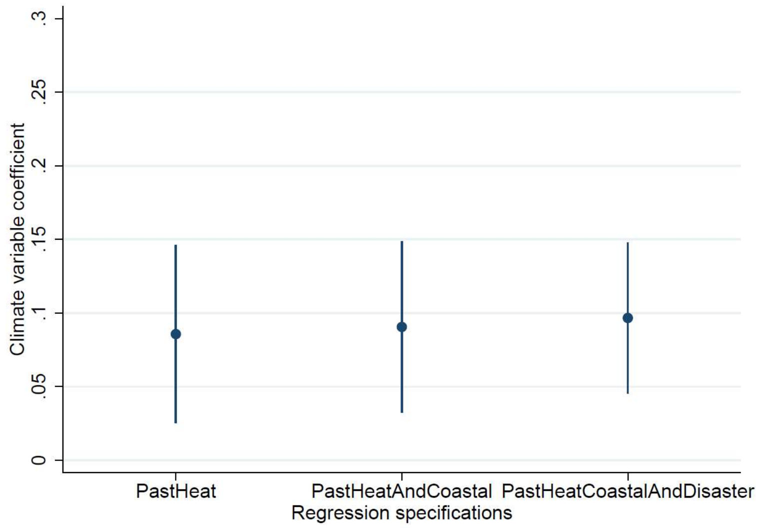
Table 12 Regressions: Subsamples without the hottest and the least hot counties

	(1) Drop +&-10pc	(2) Drop +10pc	(3) Drop - 10pc	(4) Drop +20pc	(5) Drop - 20pc
Diff2048_RCP4.5_90F (days)	.115***	.1041***	.0604*	.0788***	.0603*
	(.0231)	(.022)	(.0312)	(.0288)	(.0363)
Controls	Yes, see notes				
Observations	1546605	1664277	1876364	1527119	1619502
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 percent, specification 2 (3) drops the highest (lowest) 10 percent, whereas specification 4 (5) drops the highest (lowest) 20 percent. 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. Heteroskedasticity-consistent standard errors in parentheses are clustered at county-level.*** p<.01, ** p<.05, * p<.1.

To provide further confirmation that current climate conditions or recently experienced weather phenomena are not the drivers of my results, I add controls for the recently experienced average number of hot days and the number of natural disasters to the baseline regression. Additionally, I 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 (Figure 11).

Figure 12 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), group 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. Heteroskedasticity-consistent standard errors are clustered at county-level. The dots represent the point estimate while the lines correspond to the 95% confidence intervals.

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, I perform a simple check in which I 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, my 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. I test this alternative hypothesis in Table 13: my 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 7 and 9.

Table 13 Checking for recent market heat

	(1)	(2)	(3)	(4)
Diff2048_RCP4.5_90F	.0723***	.0838***	.0122	.0194
	(.0229)	(.0217)	(.0317)	(.0317)
Diff2048_RCP4.5_90F* Non-bank			.1412***	.1452***
			(.0259)	(.0264)
Extreme no hot days	8.1692***	9.2388***	3.2435***	4.2497***
	(2.0331)	(1.9508)	(.9016)	(.8864)
Extreme no hot days* Non-bank			10.2440***	10.0940***
			(2.3859)	(2.5083)
Recent market heat	.0793***	.1241***	.0907***	.1337***
	(.0235)	(.0244)	(.0271)	(.0199)
Non-bank*recent market heat			-.0053	-.0015
			(.0296)	(.0299)
Non-bank			-10.2376***	-10.3115***
			(1.2273)	(1.2510)
Local house price volatility	.0520***		.0536***	
	(.0158)		(.0182)	
Other controls	Yes, see notes	Yes, see notes	Yes, see notes	Yes, see notes
Observations	1990095	1997978	834517	836862
R-squared	.4076	.4071	.3888	.3882

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 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 per cent of counties and equivalent to at least 165 days with maximum temperatures above 90°F. Recent market heat variable measures the house price growth in real terms between 2012 and 2017. 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. In specifications

2 and 4 I remove the local house price volatility control on account of its correlation with the recent market heat control. In specifications 3 and 4 I add a non-bank interaction term with the recent market heat control – for these specifications I use the subsample where I have identified the type of lender. I use Buchak et al. (2018)'s classification list of the largest bank and non-bank lenders. Other 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, local competition) and the constant are omitted from the table for presentational purposes. Local competition is measured as the share of the top 10 lenders in a county. Lender dummies are included in specifications 1 and 2. In specifications 3 and 4 instead of lender dummies I include a lender rate spread which proxies lender efficiency and profit margin and is calculated as the mean rate spread on the other loans originated by the same lender. Heteroskedasticity-consistent standard errors in parentheses are clustered at county-level. *** p<.01, ** p<.05, * p<.1.

I 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 (Table 14). I add controls for unemployment and average wage in the years after the year of loan origination (2018): looking one year ahead (specifications 1-2) or to the next three years (specifications 3-4). Given the stable macroeconomic conditions experienced in 2018 and 2019, the 2019 actuals may be a reasonable proxy for market expectations from 2018 in respect of 2019. I show results for baseline specifications without and with the extreme number of hot days dummy (specifications 1 and 3, and 2 and 4, respectively). 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.

Table 14 Local time-varying economic conditions

	(1)	(2)	(3)	(4)
Diff2048_RCP4.5_90F (days)	.0584**	.0709***	.0740**	.0984***
	(.0280)	(.0241)	(.0345)	(.0223)
Extreme no hot days dummy		7.9131***		10.5332***
		(2.1965)		(2.2576)
Future wage	-.0035*	-.0033*	-.0037*	-.0032*
	(.0020)	(.0020)	(.0020)	(.0019)
Future unemployment	1.9055***	1.7486***	1.5288***	1.7464***
	(.3282)	(.3388)	(.3179)	(.2545)
Controls	Yes, see notes	Yes, see notes	Yes, see notes	Yes, see notes
Observations	1994036	1994036	1994036	1994036
R-squared	.4078	.4083	.4079	.4088
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: the projected increase in the number of days with maximum temperatures above 90°F, 2048 compared with the 2003-2012 average. Additionally, specifications 2 and 4 include 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. Controls are identical to those in the baseline regression in Table 2 except for the macroeconomic controls. Instead of average wage and unemployment figures for 2018, specifications 1 and 2 use such data from 2019 and specifications 3 and 4 use the averages between 2019 and 2021 (2020 and 2021 wage data are measured in year 2019 dollars to avoid the impact of inflation on the averages). 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, 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. Heteroskedasticity-consistent standard errors in parentheses are clustered at county-level. *** p<.01, ** p<.05, * p<.1.

Finally, I 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 (Table 15, specification 4). The result is not at odds with my findings for the length of the loan in Table 8. For areas most exposed to the rising number of hot days I thus find shorter maturities or higher interest rate premia at longer maturities.

Table 15 Regressions: Further climate controls and loan interaction

	(1) Past heat	(2) Past heat & coastal	(3) Past heat, coastal & disaster	(4) Loan term interaction
Diff2048_RCP4.5_90F (days)	.0857***	.0905***	.0967***	-.0904*
	(.0308)	(.0296)	(.0261)	(.0488)
Past heat (base: 1)				
Past heat 2	-.2196	-.3092	-.4544	
	(.6584)	(.6462)	(.6326)	
Past heat 3	-3.4356***	-3.6208***	-3.698***	
	(.7774)	(.7623)	(.7453)	
Past heat 4	-2.3937***	-2.5439***	-2.6538***	
	(.8383)	(.8196)	(.839)	
Past heat 5	-.4049	-.5823	-.1163	
	(1.041)	(1.0322)	(1.0135)	
Past heat 6	2.859*	2.37*	2.7764**	
	(1.5214)	(1.4115)	(1.3421)	
Coastal		-.9981	-.1489	
		(.6124)	(.5895)	
Past disaster (base: 1)				
Past disaster 2			2.4154**	
			(.9515)	
Past disaster 3			1.0855	
			(.9047)	
Past disaster 4			-.2954	
			(.7758)	
Past disaster 5			-1.5955*	
			(.9477)	
Past disaster 6			-.2399	
			(.9046)	
Diff2048_RCP4.5_90F *loan term				.0004***
				(.0002)
Controls	Yes, see notes			
Observations	1994036	1994036	1994036	1994036
R-squared	.4086	.4086	.4089	.4077
Lender dummies	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 are the climate variable and its interaction term with the loan term. The climate variable included is the projected increase in the number of days with maximum temperatures above 90°F, 2048 compared with the 2003-2012 average. 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), group 5 and 6 include 10% of counties each. Specification 4 adds the climate variable – loan term interaction term. 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 Heteroskedasticity-consistent standard errors in parentheses are clustered at county-level.*** p<.01, ** p<.05, * p<.1.

5.4.4. Mortgage denials by exposure to future heat increases

My results showing increased mortgage rates in areas most exposed to future heat increases have thus far focused on the universe of originated loans. If lenders' rejection behaviour, however, differs by areas' future heat exposure, my results would be subject to selection bias.

To test rejection behaviour I apply Keys and Mulder (2020)'s equation to my sample and add my climate variable. I estimate the following linear probability model for loan application i for a property in county j for subcategories $l \in$ {conforming loans (to GSE criteria), non-conforming loans}:

$$\begin{aligned} Denial_{ilj} = \alpha^l + \lambda_0^l Climate\ variable1_j \ + \lambda_1^l \sum_{n=1}^{2} Value_i^n + LTI_i^n \\ + (|CLL_j - \ Value_i\ |)^n + X_{ij}^T \lambda_2^l + \epsilon_{ilj} \end{aligned} \tag{3}$$

where Denial is the probability that the loan application is denied. Value is the inverse hyperbolic sine (IHS) of loan value, LTI is loan to income, and CLL is the local limit for conforming loans. The constant and the slope coefficients vary by whether the loan is conforming or non-conforming. X_{ij} is a k x 1 vector with k>1, λ_2 is a k x 1 vector of constants, and k denotes the number of control variables in the equation. In specification 1, controls are aligned to those applied by Keys and Mulder (2020): whether applicant is non-white, the property is the owner's primary residence, and lender is local. In line with Keys and Mulder (2020), a lender is considered local of a county, if it originates at least 10% of its total annual lending there (as measured in full HMDA data). In specification 2 I add further and more granular controls: the applicant's race, ethnicity and sex, whether they are over 62, the debt to income ratio (in buckets), and the median family income in the census tract of the property.

Table 16 Mortgage denials

	(1)	(2)
Diff2048_RCP4.5_90F	.0009***	.0005***
	(.0001)	(.0001)
Diff2048_RCP4.5_90F* conforming loan	-.0004***	-.0002***
	(.0001)	(.0001)
Observations	2658875	2185120
% of accurate prediction	90	94
% of true reject predictions	30	67
% of true accept predictions	92	95

Linear probability model that estimates the probability of a loan application being denied. Controls include IHS of loan value, LTI, CLL, applicant race, primary residence and local lender. Specification 2 also includes controls for applicant's ethnicity and sex, age, DTI and medium family income of the area.

According to my results, rejections are somewhat more probable in areas most exposed to increases in hot days. The effect is statistically and economically significant though not very large in size. One more projected hot day corresponds to a 0.03% higher probability of rejection in the case of a conforming loan under specification 2 which applies the more complete set of controls (calculated as 0.0005-0.0002). Overall 8.6% of loan applications are denied in my sample.

This result is consistent with accepted applications of somewhat higher quality in areas more exposed to heat projections as lower-quality applications may be rejected in high heat exposure counties while accepted in lower heat exposure counties. I argue that this results in a negative bias to the Climate coefficient in Case study 2's baseline regression. In other words, the effect of a higher number of extreme heat days would be even greater than that suggested by the baseline regression without the selection bias.

5.5. Conclusions from the case study

Considering a range of controls and potential sources of bias, I find that larger projected increases during the coming decades in the number of hot days 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, the case 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).

6. CASE STUDY 3: GSE SECURITISATION AND MULTIDIMENSIONAL CLIMATE CHANGE RISK

6.1. Overview of the case study

I investigate whether US residential mortgage lenders respond to climate change projections by offloading risk to government-sponsored enterprises (GSEs) which largely ignore global warming risks in their framework. Using difference-in-difference estimators I find that both banks and independent mortgage companies have sold proportionately more loans to GSEs in areas that are most exposed to the changing climate – based on my climate change indicator encompassing risks of extreme heat, drought and flood. The observed relationship can be traced back to 2013 but is more marked since 2016 when granular climate change projections became public. It is only in the highly exposed areas that I observe GSE securitisation rates to be inversely related to the extent of flood insurance coverage, suggesting one may act as a substitute for the other. While mortgage lenders' increased climate change risk awareness should be welcomed, the possible shift of the risk to the public sector or the sustainability aspects from a possible cross-subsidisation of risk from lower climate risk areas should warrant further attention.

6.2. Research questions

1. Are GSE onselling rates (the proportion of originated mortgages under GSEs' conforming limit sold on to GSEs, controlling for other factors) higher in areas most exposed to climate change?
    - Hypothesis: In the case of hurricane risk there is some evidence in the literature for lenders reducing risk through GSE securitisation (Ouazad and Khan 2019). I, therefore, hypothesise that GSE onselling may be a risk mitigation strategy against a wider group of natural disasters and, more generally, climate change risk. I expect higher GSE securitisation activity in areas most exposed to climate change.
2. Has this relationship changed in the past few years?
    - Hypothesis: I expect this activity to have increased in recent years in conjunction with rising climate risk awareness and better data

availability. Keys and Mulder (2020) document an increased recognition of climate change since 2013 and downscaled climate change projections are available since September 2016.

3. Is there evidence of firm heterogeneities in GSE on-selling activity with respect to climate change exposure?
    - Hypothesis: I expect more onselling from non-banks than banks as non-banks may be more open to new datasets, including on climate change (Section 2.6.).

6.3. Background on GSEs

The GSEs that were established to help credit flow to the housing market buy mortgages and package them into agency mortgage backed securities (agency MBS) providing guarantees to MBS buyers against loan default, essentially taking on credit risk while leaving MBS buyers exposed to interest rate risk and prepayment risk (Finkelstein et al., 2018). To manage their own credit risk, the GSEs use a number of tools, such as pooling risk in MBSs for diversification purposes, applying underwriting standards, requiring mortgage insurance and flood insurance where applicable, charging fees for the guarantee they provide and possibly resorting to credit risk transfers to transfer the risk to the private market (e.g. hedge funds). Assessing the combined adequacy of all such measures goes beyond the scope of the case study, nonetheless I set out a few pieces of the puzzle below. In the context of efforts to mitigate GSEs' credit risk since the high credit losses experienced in the 2007-09 crisis (which culminated in conservatorship for two GSEs (Finkelstein et al., 2018)), there is some evidence to suggest that the consideration of climate exposure is missing in at least some parts of the process of GSE-supported lending (Ouazad and Kahn, 2019; Keenan and Bradt, 2020). First, GSE mortgage rates do not appear take into account local risk, whereas rates on private market loans do (Hurst et al., 2016). Second, the rules on the characteristics of the loans GSEs purchase (e.g. loan size, DTI limits) and the fees they charge (to lenders) in return for the guarantee are observable – and neither of these include climate change projections (FHFA, 2019). The only GSE rule that could have relevance from a climate change perspective is the requirement for properties located in a special flood hazard area (SFHA) or a coastal barrier resource system (CBRS) to have flood insurance. In any case, the designation of such areas has drawn heavy criticism on the basis that it fails to accurately reflect flood risk, especially on a forward-looking basis (e.g. Leatherman, 2018).

Key to the case study is the observation that lenders and the GSE have asymmetrical information about the default risk of mortgages with respect to climate change risk (Ouazad & Kahn, 2019; Keenan & Bradt, 2020). GSE securitisation represents an option for lenders to remove the risk from their balance sheet. Lenders will be incentivised to securitise as long as they value this option above the cost of securitisation – the difference between the profit on the mortgage without and with securitisation. More formally for lender *l* in area *j* in respect of mortgage *i*:

$$\gamma_{l,j,i} = \begin{cases} 1 & if \;\; \xi_{l,j} - \left(\pi_{originate\,\&\,hol\;\;,l,j,i} - \pi_{originate\,\&\,securitise,l,j,i}\right) > 0 \\ 0 & if \;\; \xi_{l,j} - \left(\pi_{originate\,\&\,hol\;\;,l,j,i} - \pi_{originate\,\&\,securitise,l,j,i}\right) < 0 \\ 0 \; or \; 1 & if \; \xi_{l,j} - \left(\pi_{originate\,\&\,hold,l,j,i} - \pi_{originate\,\&\,securitise,l,j,i}\right) = 0 \end{cases} \quad (3)$$

where γ=1 denotes the action (1 for GSE securitisation, 0 for no GSE securitisation), ξ the perceived value of the removal of default risk associated with local climate change, and π the profit associated with the mortgage.

6.4. Data and methodology

6.4.1. Data

A general discussion of Climate and mortgage data is included in Section 3. GSEs only purchase loans that meet their criteria – including on the loan amount. I source county and year-specific conforming loan limit data from the Federal Housing Finance Agency (FHFA) to exclude loans from the dataset that exceed this limit. County-level house price indices are also provided by the FHFA which I use to calculate the county-level house price volatility metric.

I turn to the Federal Emergency Management Agency (FEMA) for data on Presidential disaster declarations. I include those related to natural disasters only. I use this information as a control for past riskiness – lenders may be reacting to past events rather than anticipating climate change.

I use county-level data on unemployment from the US Bureau of Labour Statistics as a macro control. I make adjustments to the data, relying on the US Census Bureau, to take account of the changes to counties (e.g. new FIP code) during the period of the study. The impact of climate change through sea level rise is beyond the scope of the case study. I therefore exclude affected counties – which I identify as those included in the NOAA SLR database. For lender heterogeneity the analysis relies on categories from CFPB (2020).

To examine GSE as an alternative to insurance, I turn to flood insurance data. The vast majority of flood insurance policies are provided for through the government's National Flood Insurance Program (NFIP) (Kousky, 2018). Policy-level NFIP data from FEMA together with annual county-level data on housing unit estimates from the US Census Bureau are used to construct the flood insurance coverage index (the proportion of housing units insured by NFIP in a county in a year).

6.4.2. Overview of methodology

The challenges I face in studying the effects of climate change are similar to Keys and Mulder (2020) and I apply a similar estimation strategy. Forecasted changes in the climate may be correlated with the number of previous disasters and other past or current climate, macroeconomic and demographic variables. The main methodology applies a difference-in-difference style estimator using observable characteristics and exploiting the trend break in climate risk awareness in 2013, similar to Keys and Mulder (2020). In the US, there were a number of events that drew public attention to climate change around 2013. Hurricane Sandy struck the East Coast in late 2012, the UN's IPCC AR5 report was published that advocated for urgent action and warned of severe and irreversible impacts, and local news coverage of climate risk grew (Keys & Mulder, 2020). With climate change increasingly salient, the issue is seen as increasingly important by the American public (Marlon et al., 2022). I compare changes in the trends of securitisation after 2013 between more climate-exposed and less climate-exposed areas, always relative to baseline values (2007-2012). I follow Emrich and Cutter (2011) in categorising counties based on their climate exposure, discussed in Section 6.4.3. For each more-climate exposed county I assign a less climate-exposed counterpart using two methods: the synthetic control method (Section 6.4.4.), which is the baseline specification, and the nearest neighbour method for robustness (Section 6.4.5.). The purpose of this matching is to find or synthetically create a counterpart (for each climate-exposed county) that is as similar as possible to the climate-exposed county up to 2012 across a range of domains – past climate, macroeconomic, demographic etc. – and in which county securitisation trends would have followed a similar pattern had it not been for the fact that one is a high climate change county whereas the counterpart is not (parallel trends assumption). The advantage of the synthetic control method is that in the absence of a large population with close matches between treated and untreated observations, more appropriate matches can be obtained by the synthetic creation of counterparts. Abadie (2021, p. 393) puts it this way: "The synthetic control method is based on the idea that, when the units of observation are a small number of aggregate entities, a combination of unaffected units often provides a more appropriate comparison than any single unaffected unit alone. The synthetic control methodology seeks to formalize the selection of the comparison units using a data driven procedure."

In any case, for robustness I also apply the nearest neighbour method in conjunction with the above-mentioned difference-in-difference estimator, and, separately, a simple pooled regression using OLS estimation (Section 6.4.5.).

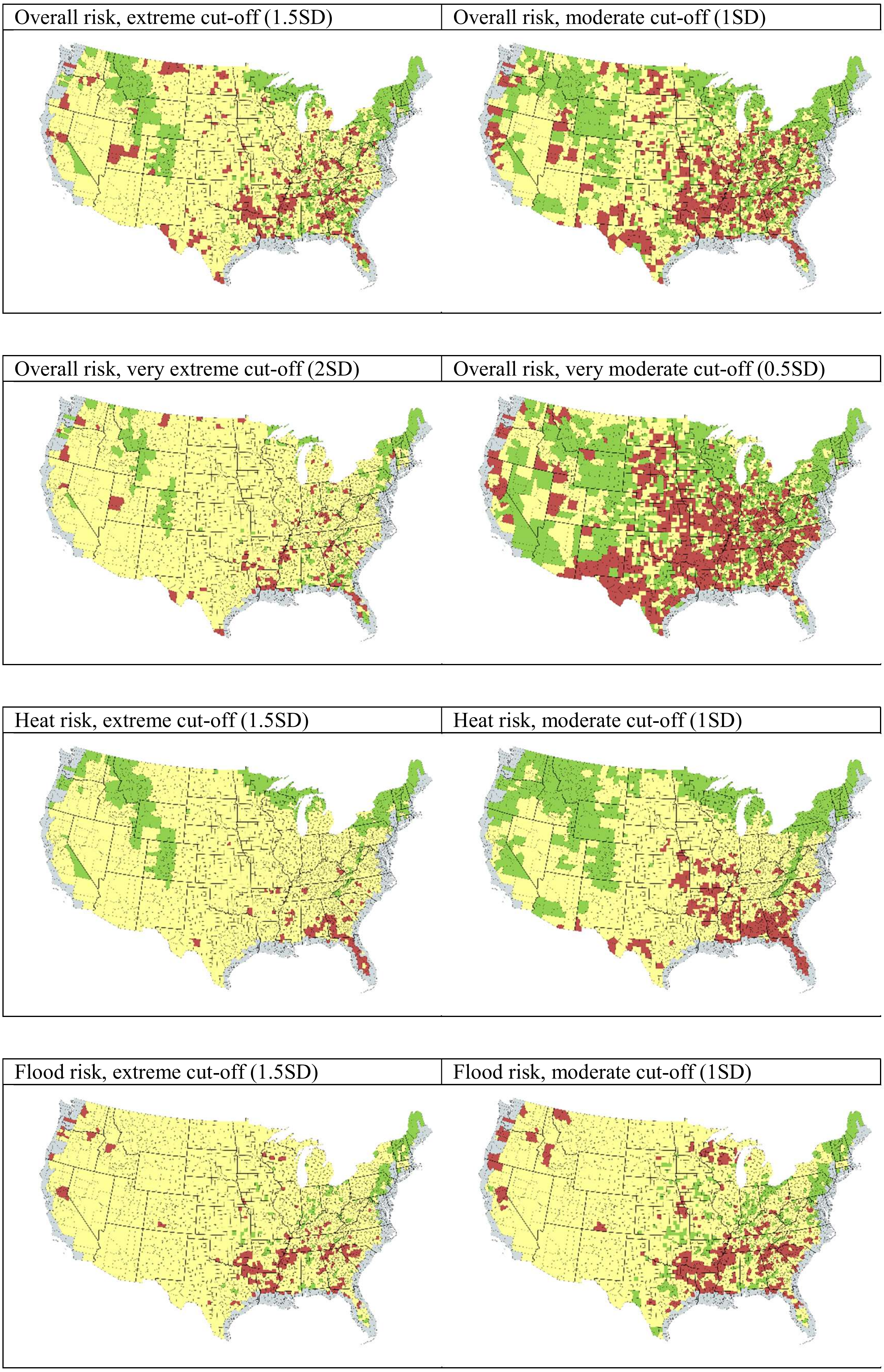
6.4.3. Climate change indicator

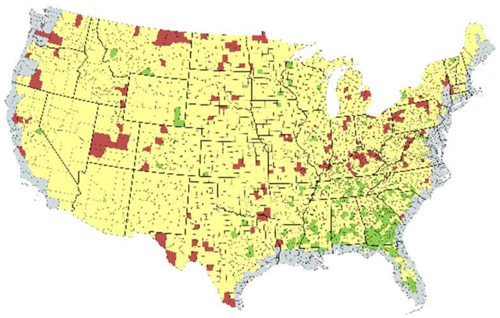
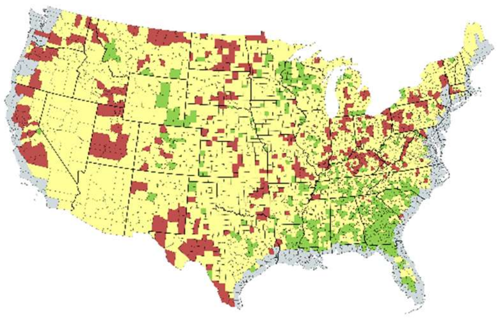
Much of the analysis relies on labelling counties according to the extent of climate change projected. I look at the following climate risk dimensions: drought, heat and flood by using ACIS data on: 1) the number of drought days per annum (when precipitation is less than 0.01 inch), 2) the number of flood days per annum (when precipitation exceeds 1 inch) and 3) the number of hot days per annum (when temperature exceeds 90°F). Thresholds are consistent with those in NOAA's Climate Explorer website. I rely on the three-class standard deviation statistical approach in Emrich and Cutter (2011) and perform categorisations at an individual risk level as well as a combined risk level as follows. For each individual risk category $r \in$ {drought, flood, heat} and county i:

$$Climate\ change\ indicator_{r,i} = \begin{cases} 3\ (high) & , \quad \delta_{ir} \geq \mu_r + \alpha * \sigma \\ 2\ (medium) & , \quad \mu_r - \alpha * \sigma < \delta_{ir} < \mu_r + \alpha * \sigma \\ 1\ (low) & , \quad \delta_{ir} \leq \mu_r - \alpha * \sigma \end{cases} \tag{4}$$

Where δ represents the projected increase in the number of hot/wet/dry days, comparing 2041-2050 projected averages with recent (2003-2012) historical averages; μ is the risk category-specific mean of δ, σ is the risk category-specific standard deviation of δ, and α is a constant. I examine results at various values of α: 0.5 (very moderate cut-off), 1 (moderate cut-off), 1.5 (extreme cut-off) and 2 (very extreme cut-off). To construct a multidimensional score (for each α separately), I sum up climate change indicators across individual risk dimensions which result in a potential maximum of 9 (3*3) and minimum of 3 (3*1). The multidimensional score is then classified into three categories using the three-class standard deviation method outlined above, resulting in an overall (cross-risk category) climate change indicator of high, medium and low. Figure 13 depicts the spatial distribution of the individual as well as the combined risk categories

Figure 13 Climate change indicator maps



Drought risk, extreme cut-off (1.5SD)	Drought risk, moderate cut-off (1SD)
	

Red, yellow and green denote high, medium and low climate change indicator counties, respectively using a three-class standard deviation method. Very moderate, moderate, extreme and very extreme cut-offs use 0.5, 1, 1.5 and 2 standard deviations as cutoffs. The higher the cutoff, the lower the number of counties in the high and low categories. Software: mapchart.net

Although the vast majority of US counties are expected to experience a rise in the number of hot days in the decades to come, the extent of the rise is particularly marked in south-eastern US while minimal increase, if any, is modelled for the mountainous areas of The Rocky Mountains, Sierra Nevada and the Appalachian Mountains as well as for the vicinity of the Great Lakes in the northern part of the country.

Topography also matters for the change in the extremes in precipitation patterns – floods and droughts. Much of the south-east – Louisiana, Mississippi, Alabama, Arkansas, Tennessee and Florida – and the northwestern coast – area of the Cascade Range and west of it – already encounter a comparatively high level of precipitation due to topography and wind directions (NOAA Climategov, 2023). Looking ahead, especially in the south-east but also in pockets in the north-west, we see the expected number of days with a high level of precipitation (flood risk) rise. The number of days with minimal precipitation (drought risk) is expected to decrease in the (south-eastern) Coastal Plains but the risk of drought rises north-west of this area (northwest of the Appalachian Mountains and of the Ozark plateau).

Combining the dimensions of flood, drought and heat projections, shows that low climate change indicator counties (LCCICs) are scattered across the South-East and the North-West in addition to the counties in the Rocky Mountains, the Appalachian Mountains, Sierra Nevada and some of those near the Great Lakes. High climate change indicator counties (HCCICs) are found scattered across the country, especially though not limited to the South-East.

6.4.4. Synthetic control method

As mentioned, the primary methodology in this case study is the synthetic control method which involves comparing HCCICs with synthetically fabricated controls from LCCICs.

The synthetic controls are created so they are as similar as possible to the HCCIC across a number of covariates and GSE rates up to 2012. I assume parallel trends thereafter and apply a difference-in-difference estimator to observe whether GSE rates differ between the HCCIC and the synthetic low climate change indicator counties (SLCCICs). More formally, I conduct the following steps building on the literature (Keys and Mulder 2020; Cavallo et al. 2013; Abadie et al. 2010).

First, for each HCCIC I identify a donor pool consisting of the 150 LCCICs with 2007-2012 average securitisation rates closest to the HCCIC's. Beyond gaining computational efficiency, restricting the comparison group to counties that are similar in the outcome variables to the HCCIC can reduce interpolation biases (Abadie et al., 2010). Then I seek to find weights through minimising the following:

$$min\colon \sqrt{(X_1 - X_0W)'V((X_1 - X_0W)} \qquad (5)$$

$$\text{subject to: } \sum_{i=1}^{150} w_i = 1$$

Where X_1 is a vector of pre-intervention characteristics for the HCCIC and X_0 is a matrix with the same variables for the donor pool. W denotes the vector for weights, which are chosen to minimise (5). V can be any symmetric and positive semidefinite matrix. I use 10 covariates and 3 outcome variables for matching purposes. I cover the macro economy (unemployment rate), lenders' risks and market environment (house price volatility and a metric that measures the average geographical concentration of lenders in the county), the type of property (owner-occupied properties' share) and demographic characteristics (share of Latinos, African Americans). I also include the recent number of disasters and historical weather variables (average number of hot, wet and dry days) to ensure results will indicate reactions to future projections rather than to past events. The three outcome variables are the average GSE securitisation rate for 2007-2008, 2009-2010 and 2011-2012. Table 17 shows descriptive statistics for variables and includes more detail on calculations.

Each variable used in the matching process is normalised (Z-score) so as to remove the influence of variables' scale-related differences. With the weights gained from the optimisation process I construct the synthetic counties and calculate their GSE percentages for years *t*:

$$SCGSE_t = \sum_{i=1}^{150} w_i * LCCGSE_{i,t} \qquad (6)$$

Where SCGSE denotes the GSE securitisation rate for the synthetic county and LCCGSE the GSE rate pertaining to each low climate change county in the donor pool. Then, similar to Keys and Mulder (2020), I calculate the following difference-in-difference style treatment effect for each year:

$$\left(\frac{HCCGSE_t}{HCCGSE_{2007-2012}} - \frac{SCGSE_t}{SCGSE_{2007-2012}}\right) \qquad (7)$$

Where HCCGSE and SCGSE denote the GSE securitisation rate for the HCCIC and its synthetic counterpart, respectively. 2007-2012 refer to averages over these years. I compare each county to its 2007-2012 average to adjust for pre-existing differences in GSE levels across counties. Repeating this process for each HCCIC allows the calculation of the cross-county average treatment effect.

Confidence intervals are calculated as follows, following Keys and Mulder (2020) and Cavallo et al. (2013): I create a synthetic control county using the same process as above for each LCCIC from other LCCICs. I then calculate treatment effects for each year for each LCCIC. Then for each year I construct 10,000 bootstrap samples from these placebo treatment effects such that each bootstrap sample size equals the number of HCCICs. The confidence intervals show us where the average placebo effect is each year with a 95% probability.

To address concerns related to results driven by highly imperfect matches between HCCICs and the synthetically created control counties, as a robustness check I drop the 25 percent of high climate change indicator counties (and the corresponding synthetic controls) where this matching results in the highest figures for Equation 5. When calculating confidence intervals, I use the same cutoff to drop „bad matches" between the low climate change indicator counties and their synthetically created counterparts.

6.4.5. Other methods

As a further robustness check, I also examine treatment effects using the nearest neighbour matching method following Keys and Mulder (2020). The method aims to match each HCCIC with a single LCCIC by minimising the Mahalanobis distance metric over a set of covariates (X):

$$min: (X_{HCCIC} - X_{LCCIC})' \sum (X_{HCCIC} - X_{LCCIC}) \quad (8)$$

Where $\sum$ is the covariate matrix. The weights are the inverse of the covariates' variance–covariance matrix. The treatment effect is estimated as the mean difference in outcomes between the HCCICs and their matched LCCIC counterparts. The assumption is that trends in the matched counties are parallel and any difference arises from the fact that climate change in one is projected to be larger than in the other. I match according to the same covariates as in the synthetic control method – excluding the outcome variable (GSE). Using more than one continuous covariate introduces large-sample bias, which I adjust for, as suggested by Abadie and Imbens (2006) and Abadie and Imbens (2011).

A simple pooled regression model with OLS estimation provides for a further robustness check. The advantage of this simple method is that it can be run at a loan level with more granular controls. The outcome variable is whether the loan was sold to a GSE or not.

Finally, I use fixed effects panel regression to study the relationship between GSE securitisation rates and NFIP insurance coverage. For county *i* and year *t* I estimate:

$$GSE_{i,t} = \alpha_i + \beta_{NFIP,it} NFIP_{it} + \beta_{1,it} X_{1,it} + \cdots + \beta_{7,it} X_{7,it} + \delta_t + \epsilon_{it} \quad (9)$$

Where GSE denotes the GSE securitisation rate, $X_{1\text{-}7}$ the key macroeconomic, market environment, demographic and disaster controls – similar in definition to those used in the synthetic control method. County and year fixed effects are included. I have performed a test for cross-sectional dependence (in particular relying on the Frees test as suggested in De Hoyos and Sarafidis (2006). Results do indeed suggest cross-sectional dependence. I therefore use Driscoll and Kraay (1998) standard errors which are robust to general forms of cross-sectional and temporal dependence and heteroskedasticity (Hoechle, 2007).

To further increase the robustness of the analysis, in separate specifications I deal with unit roots. Baltagi (2021) suggests that in micro panels with large N and small T non-stationarity is less of a concern. The various samples I use in my fixed effects panel regressions have large N (>100 up to several hundred counties) while small and fixed t-s (9 years). Nonetheless, I perform panel unit root tests. I apply the Harris–Tsavalis test that is appropriate for large N and fixed T-s (Baltagi, 2021). To minimise the impact of cross-sectional dependence in the panel unit root test, for each time period the mean of the series across panels is calculated, and this mean is subtracted for the series, following Levin et al. (2002) (demeaning). For the variables where we cannot reject the null hypothesis of unit roots, I take first differences and rerun the regression as a new specification. Taking first differences shortens the time period (8 instead of 9), I therefore include this specification as a robustness analysis.

Table 17 Case study 3 Descriptive statistics

Panel A: Summary statistics for matching

	Year	Level	N	Mean	Std. Dev.	1st Perc.	p25	Median	p75	99th Perc.
Unemployment	2012	county	2411	7.90	2.63	3.00	6.00	7.80	9.50	15.10
House price volatility	1990-2012	county	2411	0.37	0.24	0.10	0.21	0.29	0.45	1.21
Lenders' geographical concentration	2012	county	2411	86.83	6.96	68.18	81.92	87.57	92.11	99.26
Owner-occupied	2012	county	2411	0.73	0.16	0.23	0.65	0.77	0.84	1.00
Latinos	2012	county	2411	0.03	0.06	0.00	0.00	0.01	0.02	0.29
African Americans	2012	county	2411	0.02	0.05	0.00	0.00	0.00	0.02	0.25
Recent disasters	2001-2012	county	2411	6.79	3.97	1.00	4.00	6.00	9.00	20.00
Number of hot days	2003-2012	county	2411	34.12	30.19	0.34	9.00	25.13	51.62	114.51
Number of high precipitation days	2003-2012	county	2411	5.35	3.15	0.13	2.99	5.15	7.49	12.75
Number of drought days	2003-2012	county	2411	198.40	34.24	127.08	175.94	195.38	217.90	282.08
GSE securitisation rate	2007-2008	county	2411	0.39	0.11	0.14	0.32	0.39	0.46	0.66
GSE securitisation rate	2009-2010	county	2411	0.37	0.16	0.05	0.26	0.37	0.48	0.78
GSE securitisation rate	2011-2012	county	2411	0.37	0.15	0.06	0.26	0.36	0.47	0.74

Panel B: Other variables

	Year	Level	N	Mean	Std. Dev.	1st Perc.	p25	Median	p75	99th Perc.
GSE securitisation rate	2013	county	2411	0.40	0.16	0.05	0.29	0.40	0.51	0.82
GSE securitisation rate	2014	county	2411	0.42	0.16	0.07	0.31	0.41	0.52	0.82
GSE securitisation rate	2015	county	2411	0.44	0.16	0.10	0.32	0.44	0.54	0.81
GSE securitisation rate	2016	county	2411	0.46	0.16	0.09	0.35	0.46	0.56	0.83

GSE securitisation rate	2017	county	2411	0.44	0.15	0.12	0.35	0.45	0.54	0.82
GSE securitisation rate	2018	county	2411	0.43	0.14	0.12	0.34	0.43	0.52	0.79
GSE securitisation rate	2019	county	2411	0.43	0.14	0.11	0.33	0.42	0.51	0.77
Projected change in hot days		county	2411	29.74	11.21	3.75	22.18	31.98	37.89	51.46
Projected change in high precipitation days	2041-2050 vs 2003-2012	county	2411	0.16	0.94	-2.02	-0.37	0.11	0.63	2.62
Projected change in drought days		county	2411	2.91	7.01	-13.76	-1.61	3.03	7.47	18.96

Panel C: Summary statistics for fixed effects panel regression

	Year	Level	N	Mean	Std. Dev.	1st Perc.	p25	Median	p75	99th Perc.
NFIP coverage	2010-2018	county	16286	0.01	0.02	0.00	0.00	0.01	0.01	0.09
Unemployment	2010-2018	county	16353	6.77	2.93	2.50	4.50	6.20	8.50	15.40
House price volatility	2010-2018	county	16338	0.37	0.24	0.10	0.22	0.30	0.44	1.22
Lenders' geographical concentration	2010-2018	county	16353	84.99	6.87	67.70	80.27	85.45	90.03	98.31
Owner-occupied	2010-2018	county	16353	0.76	0.14	0.30	0.69	0.79	0.86	0.98
Latino	2010-2018	county	16353	0.03	0.07	0.00	0.00	0.01	0.03	0.33
African American	2010-2018	county	16352	0.03	0.06	0.00	0.00	0.00	0.02	0.28
Recent disasters	2010-2018	county	16353	6.32	3.82	0.00	4.00	6.00	8.00	19.00

Panel D: Selected summary statistics for pooled linear regression with OLS estimation

	Year	Level	N	Mean	Std. Dev.	1st Perc.	p25	Median	p75	99th Perc.
LTI	2007-2019	loan	17,671,790	2.3	2.1	0.3	1.5	2.2	3.0	5.6
loan amount	2007-2019	loan	18,352,317	191.8	105.1	28.0	112.0	173.0	255.0	445.0
CLL-loan amount	2007-2019	loan	18,352,317	247.2	104.3	0.0	183.0	263.0	320.1	464.7
Lenders' geographical concentration	2007-2019	lender	75,113	98.3	6.9	58.6	100.0	100.0	100.0	100.0
Recent disasters	2007-2019	county	35,809	6.9	4.2	1.0	4.0	6.0	9.0	20.0
Unemployment	2007-2019	county	35,809	6.3	3.0	2.2	4.1	5.7	8.0	15.4
House price volatility	2007-2019	county	28,945	0.4	0.2	0.1	0.2	0.3	0.4	1.2

	Year	Level	N	Proportion
Ethnicity*	2007-2019	loan	16,357,801	
Latino				6.51
Other				91.83
Race*	2007-2019	loan	16,350,048	
White				88.33
African American				3.62
Asian				5.85
Joint				1.55
Gender	2007-2019	loan	17,019,629	
Male				32.44
Female				21.68
Joint				45.88
Owner-occupied	2007-2019	loan	18,352,317	
Yes				82.21
No				17.79

*Only largest categories are shown

Table 17 shows descriptive statistics for variables used in the case study. House price volatility is calculated as the difference between the maximum and the minimum of a county's real house price index, divided by the value of the index in 1990 or when first available. The geographical concentration of lenders looks at the proportion of the top 5 states' share in the lender's overall lending. When used as a county-level metric, weights are each lender's loan amounts originated. The county-level owner-occupied property/Latino/African American variables look at the proportion of loans backed by such a property/with such a borrower. Recent disasters denote the number of disasters since 2001. Hot, high precipitation, drought days are defined as greater than 90°F, precipitation greater than 1 inch, precipitation less than 0.01inch, respectively. Historical weather variables cover the annual average between 2003 and 2012. Projected change weather variables compare 2041 to 2050 annual averages with that of the aforementioned historical averages. GSE securitisation rates denote the value of loans sold to GSEs as a proportion of the total loan amount. NFIP coverage is calculated as the proportion of housing units insured by NFIP in the county.

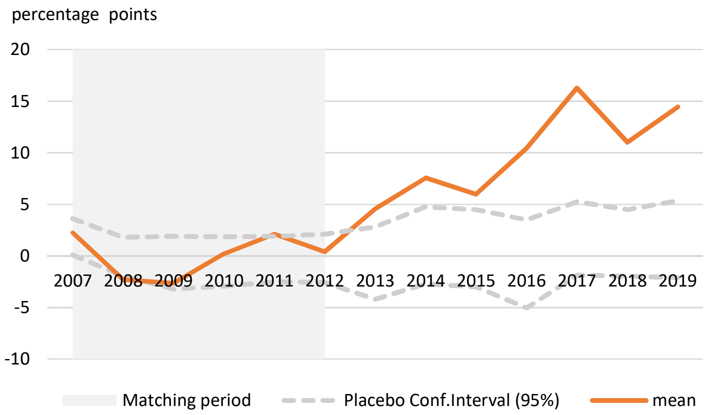
6.5. Results and discussion

6.5.1. Baseline results

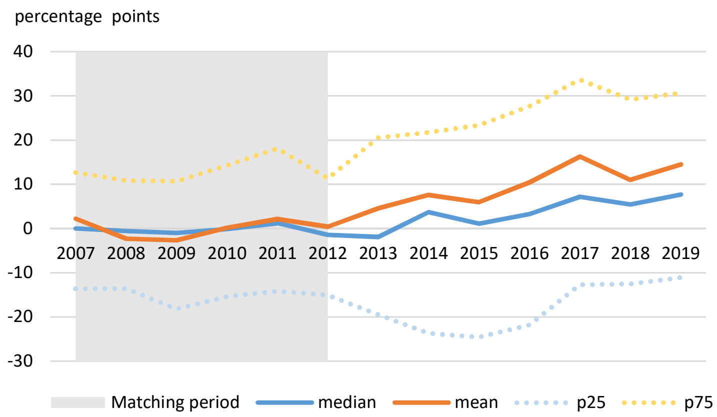
First I compare securitisation rates to GSEs between HCCICs and their synthetically created counterpart from LCCICs using the synthetic control method and for the combination of heat, drought and precipitation risk. The baseline specification shows that in recent years GSE securitisation rates in HCCICs exceeded those in their synthetic control county (Figure 14). While some difference is observable from 2013, the difference grows markedly from 2016. From 2016 to 2019 the proportion of loans sold to GSEs in HCCICs (expressed as a fraction of the county's 2007-2012 average) exceeded those in their synthetic control county by 10-16 percentage points. Treatment effects for each year from 2013 exceed the two-sided 95% interval of placebo treatment effects, suggesting statistical significance. Figure 14 Panel C shows that control counties are created such that they are much more similar to high climate change counties than the pool of low climate change counties across past macroeconomic, demographic, lender market environment, climate and disaster variables. The matching process that includes the outcome variable and a wide range of pre-2013 characteristics intends to ensure that the parallel trends assumption underlying the difference-in-difference estimation strategy holds. That is, absent the difference in climate change exposure, GSE securitisation rates across a county and its very similar synthetic counterpart would have followed a similar path. Any observed difference in GSE rates can therefore be attributed to differences in climate change exposure rather than other effects. In *Lender heterogeneity* subsection (Section 6.5.3) I gain further comfort by studying changes in lender composition in HCCICs and other counties.

Figure 14 Synthetic control with overall climate change indicator and an extreme (1.5 SD) cut-off

Panel A



Panel B



Panel C

	All	High CCI	Low CCI	SC	HCCI-SC Diff Sign.
Unempl 2012	7.9 (2.63)	8.82 (2.19)	8.44 (2.31)	8.74 (1.54)	
HP vol (up to 2012)	.37 (.24)	.33 (.22)	.43 (.27)	.35 (.16)	***
Lenders'top5 state share 2012	86.83 (6.96)	86.74 (6.85)	85.58 (6.74)	86.83 (4.89)	
Owner occ % 2012	.73 (.16)	.71 (.15)	.68 (.19)	.71 (.1)	
Latino 2012	.03 (.06)	.03 (.09)	.01 (.02)	.02 (.02)	**
Black 2012	.02 (.05)	.04 (.07)	.02 (.04)	.04 (.05)	**
Disasters 2001-2012	6.79 (3.97)	6.78 (3.84)	6.13 (4.12)	6.54 (2.64)	**
Hot days average 2003-2012	34.12 (30.19)	44.43 (29.)	22.04 (28.13)	39.98 (23.14)	***

Panel C continued

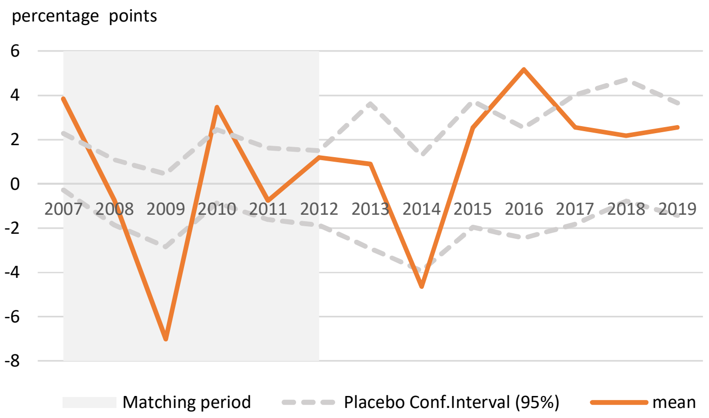
	All	High CCI	Low CCI	SC	HCCI-SC Diff Sign.
Wet days average 2003-2012	5.35 (3.15)	6.74 (2.89)	5.62 (3.56)	6.89 (2.36)	**
Dry days average 2003-2012	198.4 (34.24)	188.64 (28.45)	181.89 (31.19)	188.48 (22.86)	
GSE rate 2007-2008	.39 (.11)	.36 (.1)	.41 (.11)	.37 (.08)	**
GSE rate 2009-2010	.37 (.16)	.33 (.15)	.4 (.15)	.33 (.13)	
GSE rate 2011-2012	.37 (.15)	.34 (.14)	.4 (.14)	.34 (.12)	
No of counties	2411	307	453	307	

Figure 14 summarizes the treatment effect on GSE rates from the synthetic control method using the overall climate change indicator – which includes heat, flood and drought risk. High (low) climate change indicator (CCI) counties are defined using a three-class standard deviation method using 1.5 (-1.5) standard deviation as the cut-off. Synthetic matches have been performed on the 13 variables in the table. The table shows averages (standard deviations in brackets) for all, HCCI, LCCI and synthetic control counties. The last column shows the significance levels of a paired t test comparing means between HCCIC and SC. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Panel B shows various statistics of the treatment effect which is a difference-in-difference estimator between each HCCI county and its synthetically matched counterpart. Panel A also shows the placebo confidence interval which is calculated by matching low CCI counties with a synthetic control using the same methodology as for the HCCIC and then constructing 10,000 bootstrap samples from the placebo treatment effects.

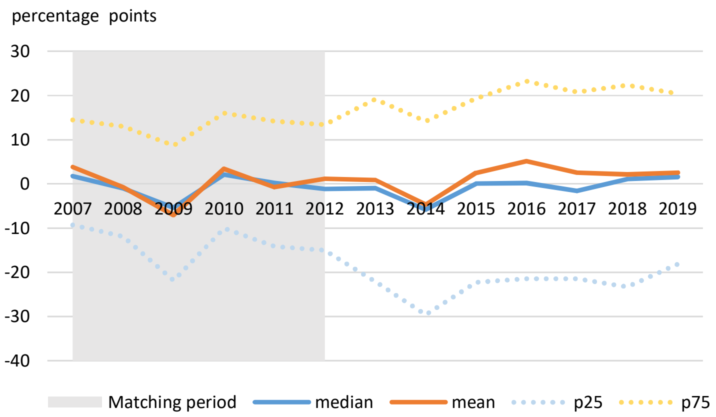
Importantly, the baseline specification applies an α of 1.5 in Equation 4 in its definition of HCCI and LCCI county. The higher the constant α, the more I am focusing on the sides of the distribution – comparing a smaller group of HCCICs with a counterpart fabricated from a smaller group of LCCICs. The smaller group of HCCICs (LCCICs) at higher α-s would have a higher (lower) average exposure to climate change than a group of HCCICs (LCCICs) defined with a smaller value of α. Logically, therefore, I would expect higher treatment effects in the case of higher α-s, reflecting the more marked difference between HCCICs and SLCCICs. Indeed, while I observe statistically significant treatment effects of up to 23% and 16% at an α of 2 and 1.5, respectively (Figures 16 and 14); treatment effects are statistically largely insignificant and below 5-7% at α-s of 0.5 and 1 (Figures 15 and 16). This suggests that GSE securitisation rates only differ at the extremes of climate change risk: lenders do not appear to give consideration to climate change risk, as reflected in GSE securitisation activity, unless the area is highly exposed.

Figure 15 Synthetic control with overall climate change indicator and 0.5 SD cut-off

Panel A



Panel B



Panel C

	All	**High CCI**	**Low CCI**	**SC**	**HCCI-SC Diff Sign.**
Unempl 2012	7.9 (2.63)	8.17 (2.57)	7.69 (2.56)	8.18 (1.91)	
HP vol (up to 2012)	.37 (.24)	.31 (.2)	.4 (.25)	.33 (.15)	***
Lenders'top5 state share 2012	86.83 (6.96)	87.67 (7.)	86.32 (6.9)	87.47 (5.38)	**
Owner occ % 2012	.73 (.16)	.72 (.14)	.72 (.17)	.72 (.11)	
Latino 2012	.03 (.06)	.03 (.06)	.02 (.06)	.03 (.06)	***
Black 2012	.02 (.05)	.03 (.06)	.01 (.03)	.03 (.05)	
Disasters 2001-2012	6.79 (3.97)	7.31 (3.95)	6.41 (3.8)	7.3 (2.97)	
Hot days average 2003-2012	34.12 (30.19)	44.69 (27.2)	25.89 (30.99)	42.25 (23.57)	***
Wet days average 2003-2012	5.35 (3.15)	6.45 (2.81)	4.74 (3.14)	6.21 (2.29)	***

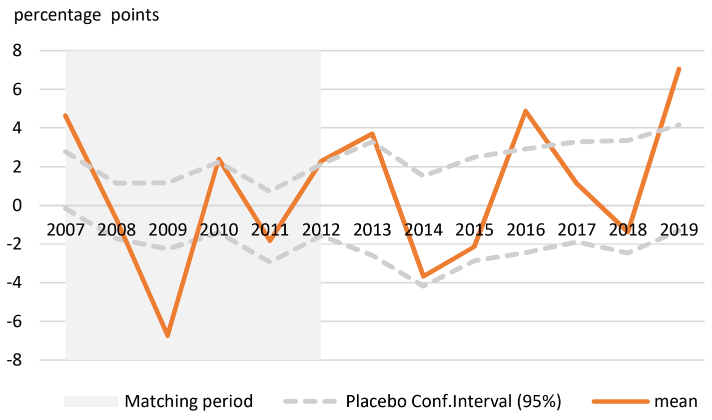
Panel C continued

	All	High CCI	Low CCI	SC	HCCI-SC Diff Sign.
Dry days average 2003-2012	198.4 (34.24)	198.31 (28.58)	196.87 (38.6)	200.14 (25.35)	***
GSE rate 2007-2008	.39 (.11)	.37 (.11)	.4 (.11)	.37 (.09)	
GSE rate 2009-2010	.37 (.16)	.33 (.15)	.4 (.15)	.34 (.14)	***
GSE rate 2011-2012	.37 (.15)	.33 (.15)	.4 (.15)	.34 (.14)	
No of counties	2411	777	995	777	

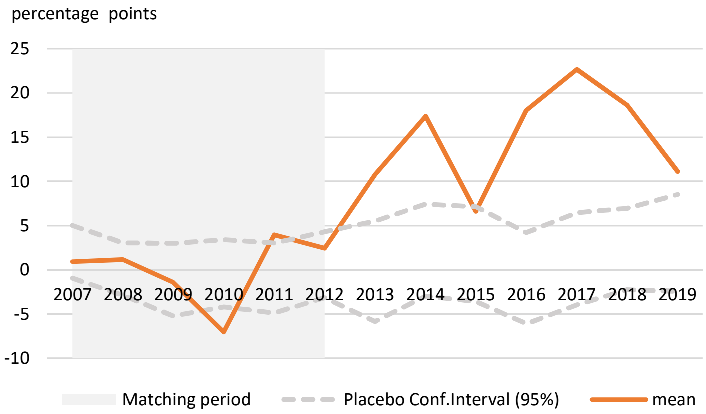
This figure summarizes the treatment effect on GSE rates from the synthetic control method using the overall climate change indicator – which includes heat, flood and drought risk. High (low) climate change indicator (CCI) counties are defined using a three-class standard deviation method using 0.5 (-0.5) standard deviation as the cut-off. Synthetic matches have been performed on the 13 variables in the table. The table shows averages (standard deviations in brackets) for all, HCCI, LCCI and synthetic control counties. The last column shows the significance levels of a paired t test comparing means between HCCIC and SC. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Panel B shows various statistics of the treatment effect which is a difference-in-difference estimator between each HCCI county and its synthetically matched counterpart. Panel A also shows the placebo confidence interval which is calculated by matching low CCI counties with a synthetic control using the same methodology as for the HCCIC and then constructing 10,000 bootstrap samples from the placebo treatment effects.

Figure 16 Synthetic control with overall climate change indicator, 1 and 2 SD cut-offs

Panel A: 1SD cut-off



Panel B: 2SD cut-off

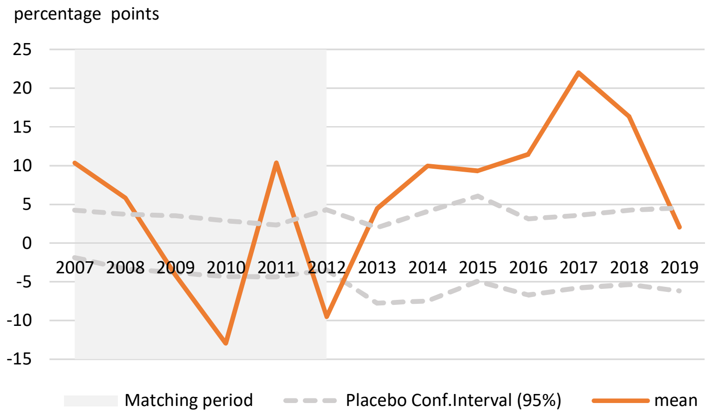


This figure summarizes the treatment effect on GSE rates from the synthetic control method using the overall climate change indicator – which includes heat, flood and drought risk. High (low) climate change indicator (CCI) counties are defined using a three-class standard deviation method using 1 (-1) standard deviation as the cut-off in panel A and 2 (-2) standard deviation as the cut-off in panel B. Synthetic matches have been performed on 13 variables up to 2012 (covering the macro economy, lenders' risks, the housing market, the type of property, demographic characteristics, recent number of disasters and past weather, as well as past GSE securitisation rates). The treatment effect which is a difference-in-difference estimator between each HCCI county and its synthetically matched counterpart. The placebo confidence interval is calculated by matching low CCI counties with a synthetic control using the same methodology as for the HCCIC and then constructing 10,000 bootstrap samples from the placebo treatment effects. Panel A (1 SD) is based on 571 HCCIC and 729 LCCIC while Panel B (2 SD) is based on 140 HCCIC and 204 LCCIC.

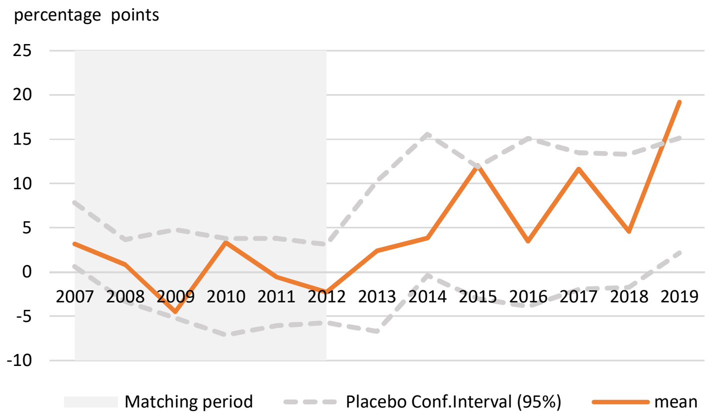
I also provide a breakdown of risk factors. Heat and flood risk appear to be driving risk considerations (Figure 17).

Figure 17 Synthetic control with individual risk climate change indicators

Panel A: Heat



Panel B: Drought



Panel C: Flood

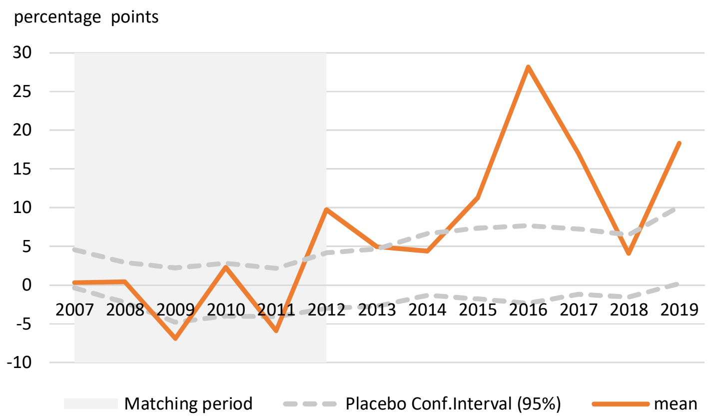


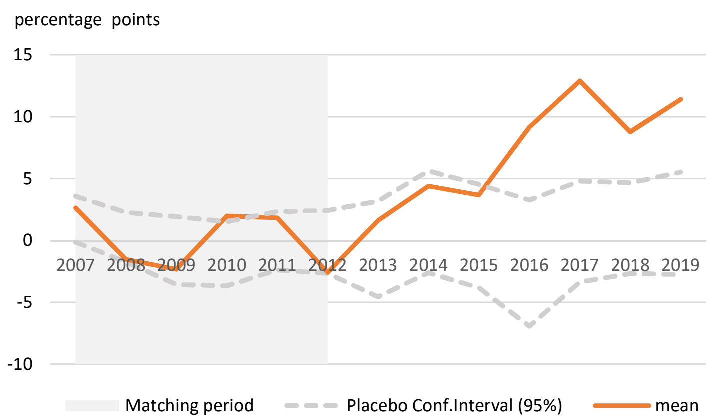
Figure 17 summarizes the treatment effect on GSE rates from the synthetic control method using the individual risk climate change indicators – heat, flood and drought risk – separately. High (low) climate change indicator (CCI) counties are defined using a three-class standard deviation method using 1.5 (-1.5) standard deviation as the cut-off. Synthetic matches have been performed on 13 variables up to 2012 (covering the macro economy, lenders' risks, the housing market, the type of property, demographic characteristics, recent number of disasters and past weather, as well as past GSE securitisation rates). The treatment effect is a difference-in-difference estimator between each HCCI county and its synthetically matched counterpart. The placebo confidence interval is calculated by matching low CCI counties with a synthetic control using the same methodology as for the HCCIC and then constructing 10,000 bootstrap samples from the placebo treatment effects.

6.5.2. Robustness tests

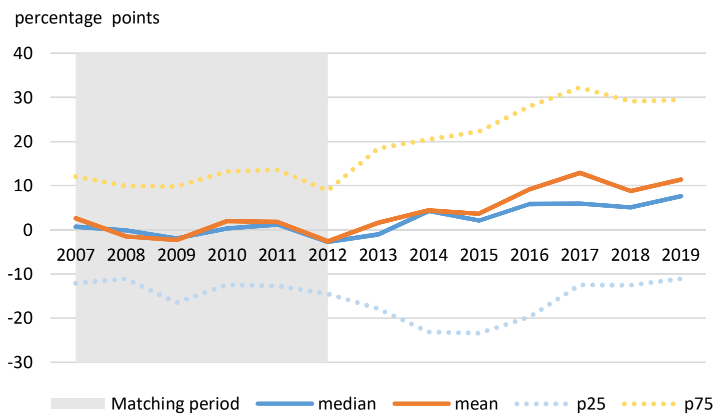
I run a battery of robustness checks. To ensure that my results are not driven by highly imperfect matches between HCCICs and their synthetic counterparts, I drop 25% of HCCICs with the worst match (Equation 5). Results continue to show economically and statistically significant treatment effects from 2016 of around 9-13% (Figure 18).

Figure 18 Synthetic control with overall climate change indicator without bad matches

Panel A



Panel B



Panel C

	All	High CCI	Low CCI	SC	HCCI-SC Diff Sign.
Unempl 2012	7.9 (2.63)	8.65 (1.78)	8.44 (2.31)	8.7 (1.41)	
HP vol (up to 2012)	.37 (.24)	.32 (.19)	.43 (.27)	.34 (.16)	***
Lenders'top5 state share 2012	86.83 (6.96)	87.14 (5.89)	85.58 (6.74)	87.09 (4.82)	
Owner occ % 2012	.73 (.16)	.72 (.14)	.68 (.19)	.71 (.1)	***
Latino 2012	.03 (.06)	.01 (.02)	.01 (.02)	.02 (.02)	**
Black 2012	.02 (.05)	.03 (.05)	.02 (.04)	.03 (.04)	
Disasters 2001-2012	6.79 (3.97)	6.35 (3.23)	6.13 (4.12)	6.35 (2.56)	
Hot days average 2003-2012	34.12 (30.19)	38.99 (25.19)	22.04 (28.13)	36.43 (22.09)	***
Wet days average 2003-2012	5.35 (3.15)	6.73 (2.81)	5.62 (3.56)	6.79 (2.4)	
Dry days average 2003-2012	198.4 (34.24)	182.94 (25.63)	181.89 (31.19)	184.27 (22.56)	***
GSE rate 2007-2008	.39 (.11)	.36 (.1)	.41 (.11)	.37 (.09)	
GSE rate 2009-2010	.37 (.16)	.33 (.14)	.4 (.15)	.33 (.12)	
GSE rate 2011-2012	.37 (.15)	.33 (.13)	.4 (.14)	.33 (.12)	
No of counties	2411	231	453	231	

This figure summarizes the treatment effect on GSE rates from the synthetic control method using the overall climate change indicator – which includes heat, flood and drought risk. High (low) climate change indicator (CCI) counties are defined using a three-class standard deviation method using 1.5 (-1.5) standard deviation as the cut-off. Synthetic matches have been performed on the 13 variables in the table. The worst matches – defined as the 25 percent of HCCIC (and their SC counties) where matching results in highest overall score in Eq. 5 – are dropped. The table shows averages (standard deviations in brackets) for all, HCCI, LCCI and synthetic control counties. The last column shows the significance levels of a paired t test comparing means between HCCIC and SC. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Panel B shows various statistics of the treatment effect which is a difference-in-difference estimator between each HCCI county and its synthetically matched counterpart. Panel A also shows the placebo confidence interval which is calculated by matching low CCI counties with a synthetic control using the same methodology as for the HCCIC (including dropping bad matches using the same threshold) and then constructing 10,000 bootstrap samples from the placebo treatment effects.

Next, as an alternative method I use nearest neighbour matching for all four α-s in Equation 4. As before, I find statistically and economically significant treatment effects when looking at the extremes (extreme (α=1.5) and very extreme (α=2) cut-offs) but not when I consider broader groups (very moderate (α=0.5) and moderate (α=1) cut-offs) (Table 18).

Table 18 Nearest neighbour matching with overall climate change indicator

	SD = 0.5		SD = 1		SD = 1.5		SD = 2	
	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
2007	1.5	1.7	0.8	2.0	0.5	2.4	-2.3	3.0
2008	-0.1	1.6	-1.3	1.6	-1.8	2.2	0.7	3.4
2009	-5.6***	1.6	-2.4	1.8	0.1	2.6	-1.1	4.4
2010	0.5	1.8	-0.4	1.9	-1.3	2.4	-6.5*	3.8
2011	1.9	1.6	2.8	2.0	2.2	2.6	1.9	3.5
2012	1.7	1.7	0.6	1.9	0.4	2.5	7.4*	4.1
2013	0.2	2.3	3.5	2.9	7.4*	4.2	13.4**	5.6
2014	-2.6	2.3	1.0	3.1	8.3*	4.6	14.2**	6.2
2015	1.0	2.4	2.5	3.1	8.7*	4.5	5.8	6.3
2016	2.5	2.4	3.5	3.1	10.2**	4.2	15.3**	6.3
2017	1.8	2.6	1.9	3.1	8.6**	3.7	16.0***	5.9
2018	1.0	2.8	0.1	3.0	4.2	3.3	17.6***	5.2
2019	0.5	2.3	3.4	3.3	9.9**	4.1	9.9*	5.1
No of HCCIC	777		571		307		140	
No of LCCIC	995		729		453		204	

The table shows average treatment effects in percentage points between HCCI and LCCI counties using the nearest neighbour matching method. For each HCCIC the one LCCI is selected as a counterpart that closest matches the HCCIC across 13 variables which include demographic, macro-economic, market and climate variables up to 2012. Results are shown for different definitions of High and Low CCIs: 0.5, 1, 1.5 and 2 standard deviations from cross-county overall climate change indicator mean. Bias adjustment correction has been performed to correct for the large-sample bias that arises when matching on more than one continuous covariate. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

I also run simple pooled regressions with OLS estimation. By running the regression at a loan level I am able to add a more granular set of controls including the loan to income (LTI), the loan amount, the distance of the loan amount from the GSEs' conforming limit, the race, sex and ethnicity of the borrower and whether the property is owner-occupied or not. For control variables (including high order terms) I rely to a large extent on Keys and Mulder (2020). I use data from 2007 to 2019. In one specification I assume that climate projection variables start to influence lenders' securitisation behaviour from 2016 whereas in another specification this is set to 2017. There are arguments in favour of both years. Granular climate change projections became available from the second half of 2016 (USGS, 2016). But it takes time to incorporate climate change projections in systems, processes and lending practices and the indirect effects of projections on lending behaviour could take longer still. Lenders' macroeconomic, demographic and housing market expectations may be shaped by climate change without an explicit incorporation of climate projections.

For almost all risk sources and both specifications, results confirm at a high statistical significance that an increase in the projected climate change – measured across hot days, drought days and flood days – increases the probability of the loan being sold to GSEs (Table 19). For example, a 10-day higher projected increase in flood risk days is associated with a 1-2 percent higher probability of securitisation to GSEs (10* 0.0017 in specification 1 and 10* 0.0011 in specification 2).

Table 19 Pooled regression with OLS estimation

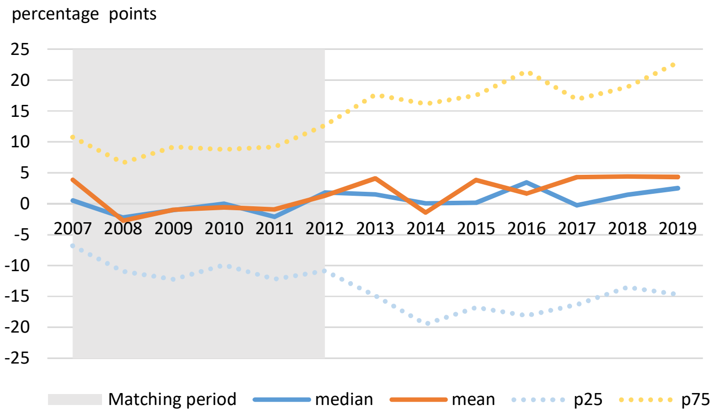
Assumed start of climate change realisation:	2016	2017
Increase in hot days	0.0000	0.0004***
Increase in flood risk days	0.0017***	0.0011**
Increase in drought risk days	0.0003 ***	0.0003***
Controls	loan, lender and borrower characteristics; macroeconomic controls and past disasters	
R squared	0.2068	0.2068
Prob > F	0.0000	0.0000
Year dummies	Yes	Yes
County dummies	Yes	Yes
Year-State Dummies	Yes	Yes
Obs	14,231,961	14,231,961

The table shows results from a pooled linear regression with OLS estimation covering the period 2007-2019. Specification 1 (2) assumes granular climate change projections exert an influence on lenders from 2016 (2017). The dependent variable is whether the loan was sold to GSEs within a year (Yes=1, No =0). Key explanatory variables of interest are: Projected change in the number of i) hot (>90°F) days, ii) flood days (precipitation >1 inch) and iii) drought days (precipitation < 0.01 inch). I compare the projected average between 2041 and 2050 with the average from recent past (2003-2012). Control variables are similar to Keys and Mulder (2020), including others often included in the literature: LTI, LTI2, inverse hyperbolic sine (IHS) of loan amount and (IHS loan amount)2, IHS(conforming limit – loan amount), (IHS(conforming limit – loan amount))2, (IHS(conforming limit – loan amount))3,ethnicity, race, sex, owner-occupied residence, lender's geographical presence, number of recent presidential disaster declarations (2001-), county unemployment rate, county house price volatility metric. In addition, dummies for the year, county as well as year-state are included. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

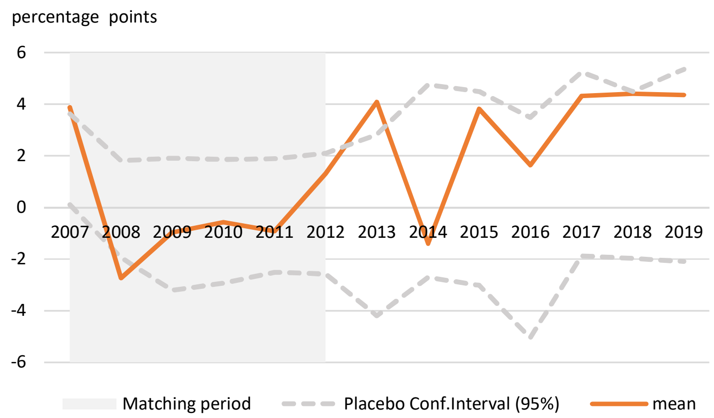
I also perform a placebo test whereby I randomly assign HCCIC and LCCIC labels to counties (regardless of whether their true exposure to climate change is high, medium or low) such that the number of HCCICs and LCCICs equals that in my baseline specification. Logically, I would not expect to see statistically significant treatment effects in the case of a random allocation which, indeed, is confirmed in Figure 19.

Figure 19 Placebo synthetic control

Panel A



Panel B



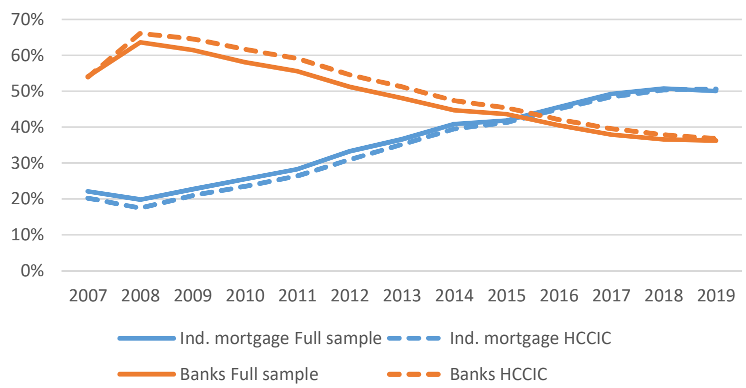
This figure summarizes the treatment effect on GSE rates from the synthetic control method using the overall climate change indicator – which includes heat, flood and drought risk. It shows the results of a placebo test in which I randomly assign high (low) climate change indicator (CCI) labels to counties such that the number of HCCI and LCCI counties equal that in my baseline specification which uses a 1.5 SD cut-off (in Figure 14). Panel A shows various statistics of the treatment effect which is a difference-in-difference estimator between each (randomly assigned) HCCI county and its synthetically matched counterpart. Panel B also shows the placebo confidence interval calculated from (true) low CCI counties.

6.5.3. Lender heterogeneity

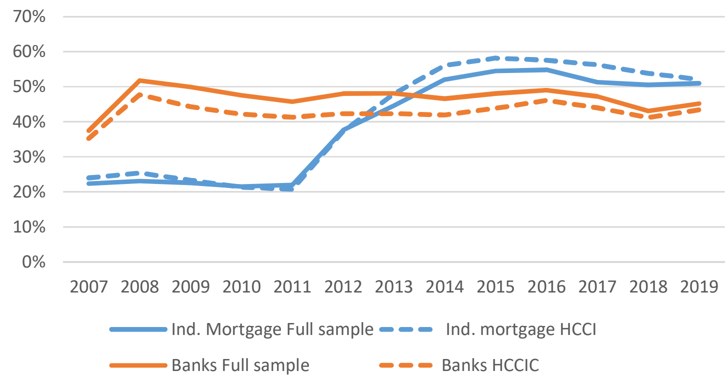
Non-banks, in particular independent mortgage companies, have increased their market share significantly in the past decade as banks' share has come down (Figure 20 Panel A). In recent years independent mortgage companies' GSE securitisation rate has been higher than that of banks (Figure 20 Panel B). A valid question, therefore, is whether higher securitisation rates in HCCICs reflect composition effects. In other words, is comparatively more independent mortgage company lending happening in HCCICs – which may or may not be independent of climate change concerns, or are certain lenders more likely to sell their HCCIC loans to GSEs compared to their loans elsewhere? Should there be marked changes in the composition of lenders between HCCICs and LCCICs, it may also call into question the parallel trends assumption underlying the difference-in-difference estimation strategy in *Baseline Results* subsection. The shift in market share, however, is broadly the same in my full sample as in the sample of HCCICs (Figure 20 Panel A).

Figure 20 Market share and GSE rates by lender type

Panel A: Market share



Panel B: GSE rates

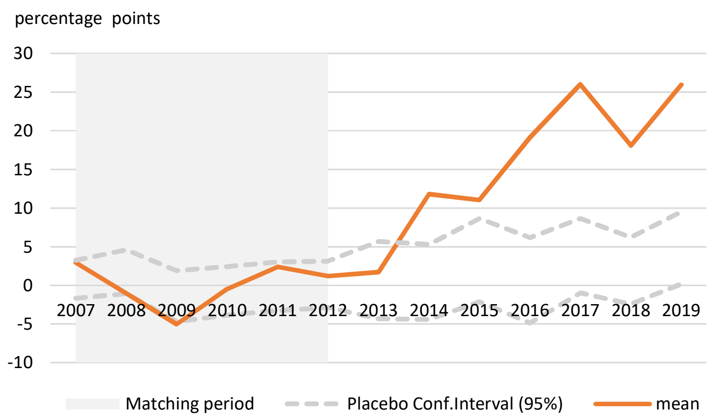


Panel A compares independent mortgage companies and banks in the sample by loan value. Panel B shows GSE rates – total value of loans sold to GSEs divided by total value of loans in my sample. Solid (dotted) line represents full sample (sample of HCCICs where HCCIC definition applies α of 1.5 in Equation 4).

Compared to their lending in the sample as a whole, independent mortgage companies sell slightly more loans to GSEs in HCCICs (Figure 20, Panel B). More formally, I investigate disparities in banks' and, separately, independent mortgage companies' GSE rates in respect of climate change exposure by rerunning the synthetic control method but only including loans in the GSE sample originated by the specific lender type. Results suggest that GSE rates are higher in HCCICs compared to LCCICs, controlling for a range of factors, in respect of both banks' and independent mortgage companies' lending (Figure 21). My analysis therefore suggests that the results are not (primarily) driven by composition effects.

Figure 21 Synthetic control: banks and independent mortgage companies

Panel A: Banks



Panel B: Independent mortgage companies

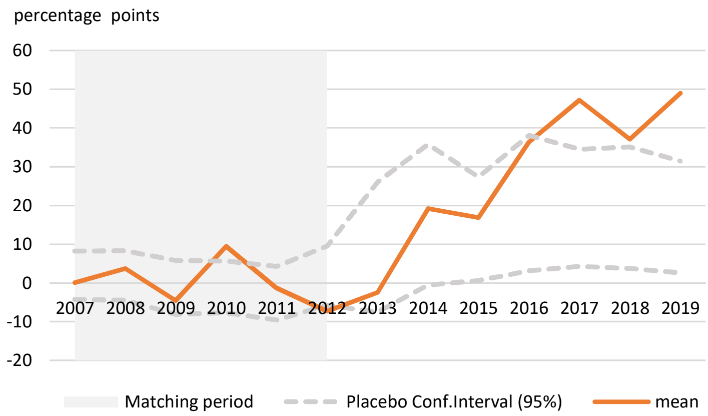


Figure 21 summarizes the treatment effect on GSE rates from the synthetic control method using the overall climate change indicator – which includes heat, flood and drought risk. High (low) climate change indicator (CCI) counties are defined using a three-class standard deviation method using 1.5 (-1.5) standard deviation as the cut-off. Synthetic matches have been performed on 13 variables up to 2012 (covering the macro economy, lenders' risks, the housing market, the type of property, demographic characteristics, recent number of disasters and past weather, as well as past GSE securitisation rates). The treatment effect is a difference-in-difference estimator between each HCCI county and its synthetically matched counterpart. The placebo confidence interval is calculated by matching low CCI counties with a synthetic control using the same methodology as for the HCCIC and then constructing 10,000 bootstrap samples from the placebo treatment effects. Panel A (B) uses bank (independent mortgage company) loans only to construct GSE rates.

6.5.4. GSE an alternative to insurance?

To gain confirmation that higher GSE securitisation rates in climate change-exposed areas are indeed driven by lenders' desire to mitigate risk, I examine GSE rates' relationship with another form of risk mitigation – reliance on flood insurance. I observe that in HCCICs NFIP coverage ratios and GSE securitisation rates have a statistically highly significant negative relationship. Higher NFIP coverage coincides with lower GSE securitisation rates. Importantly, this is only true for HCCICs – measured both by overall risk in Table 20 specification 1 and flood-specific risk in specification 3. I do not document a similar relationship in case of either LCCICs (specifications 2 and 4) or medium climate change indicator counties (untabulated). Results suggest that in areas most exposed to the changing climate lenders may view insurance and GSEs as substitutes. As for other counties, what we see is that insurance and GSE securitisation appear not to be substitutes, but there can be multiple interpretations as to what this tells us about lenders' climate risk approach. In some non-HCCICs it may reflect a view that as flood risk is low neither form of risk mitigation (GSE securitisation or insurance) is necessary. From a risk perspective this may be right or wrong. Results for non HCCICs may also mean that it is mainly one form of risk mitigation that is used and not the other (GSE securitisation is less used in these areas).

Results on HCCICs are also in line with Ouzad and Khan (2019) who document securitisation's increased option value after disasters especially where flood insurance is not required.

Table 20 GSE and NFIP

	(1) HCCIC Overall	(2) LCCIC Overall	(3) HCCIC Flood	(4) LCCIC Flood
NFIP coverage	-1.6220***	.3556	-2.0575**	2.5957***
	(.4551)	(.3379)	(.7331)	(.5906)
Unemployment	-.0001	-.0005	-.0017	-.0043
	(.0029)	(.0012)	(.0040)	(.0025)
House Price volatility	-.0245	.0282	.1121	-.0207
	(.0749)	(.1066)	(.0987)	(.0682)
Lenders' top5state share	-.0118***	-.0117***	-.0123***	-.0115***
	(.0005)	(.0005)	(.0006)	(.0004)
Owner occupied%	.1419**	.0867**	.0540	.1628***
	(.0498)	(.0315)	(.0555)	(.0473)
Latino	.0666	-.0173	.0226	-.2136
	(.0492)	(.0855)	(.1269)	(.1802)
African American	.0156	-.0719	-.0637	-.2251
	(.1087)	(.0762)	(.0829)	(.1432)
Recent disasters	.0027	-.0007	.0020*	.0043**
	(.0021)	(.0011)	(.0010)	(.0018)
Constant	1.2377***	1.282***	1.3038***	1.2104***
	(.0796)	(.0518)	(.0595)	(.0763)
Observations	2264	2856	1412	1152
Number of counties	252	318	157	128
Within R-squared	.3870	.3651	.4739	.3543
Year and County FE	Yes	Yes	Yes	Yes

The table shows outputs of fixed effects panel regressions covering 2010-2018. The dependent variable is the proportion of loans (by amount) sold to GSEs. NFIP coverage measures the proportion of housing units covered by NFIP. Recent disasters refer to the number of natural disasters in the 12 years up to and including the given year. The explanatory variables are identical to the ones used in the synthetic control method. House price volatility is calculated as the difference between the maximum and the minimum of a county's real house price index, divided by the value of the index in 1990 or when first available. The geographical concentration of lenders looks at the proportion of the top 5 states' share in the lender's overall lending. When used as a county-level metric, weights are each lender's loan amounts originated. The county-level owner-occupied property/Latino/African American variables look at the proportion of loans backed by such a property/with such a borrower. Specification 1 and 2 are based on overall risk categories – including heat, flood and drought while specifications 3 and 4 are based on flood risk only. Specification 1 and 3 (2 and 4) refer to counties with high (low) climate change indicators as per the three-class standard deviation method using 1.5 (-1.5) standard deviation as the cut-off. Driscoll-Kraay standard errors are used. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 21 provides further robustness. Baltagi (2021) suggests that in micro panels with large N and small T, non-stationarity is less of a concern – the various samples I use in my fixed effects panel regressions have large N (>100 up to several hundred counties) while small and fixed t-s (9 years). Nonetheless, in Table 21 I show results from regressions with modified variables (for variables which are not stationary I take first differences). Conclusions remain unchanged.

Table 21 GSE and NFIP with stationary variables

	(1) HCCIC Overall	(2) LCCIC Overall	(3) HCCIC Flood	(4) LCCIC Flood
NFIP coverage	-1.5852**	1.3100***	-2.6109*	3.8276***
	(.6684)	(.1703)	(1.3363)	(.4925)
Unemployment (delta)	-.0012	-.0044	.0062	-.0085**
	(.0058)	(.0027)	(.0037)	(.0030)
House Price volatility (delta)	-.2256**	-.2224*	.0513	-.2326
	(.0705)	(.1117)	(.1071)	(.1432)
Lenders' top5state share (delta)	-.0054***	-.0060***	-.0055***	-.0056***
	(.0006)	(.0003)	(.0009)	(.0005)
Owner occupied%	.1747***	.1039**	.0949	.2131***
	(.0378)	(.0440)	(.0512)	(.0341)
Latino	.0555	-.0029	.0471	-.2012
	(.0649)	(.1087)	(.1124)	(.2235)
African American	-.0352	-.0760	-.0678	-.1543
	(.1111)	(.1267)	(.0981)	(.1660)
Recent disasters (delta)	-.0015	-.0011	-.0046**	.0050*
	(.0022)	(.0012)	(.0017)	(.0022)
Constant	.2790***	.3325***	.3578***	.2259***
	(.0273)	(.0280)	(.0495)	(.0199)
Observations	2013	2539	1256	1024
Number of counties	252	318	157	128
Within R-squared	.2554	.2348	.3114	.2522
Year and County FE	Yes	Yes	Yes	Yes

The table shows outputs of fixed effects panel regressions covering 2010-2018. The dependent variable is the proportion of loans (by amount) sold to GSEs. NFIP coverage measures the proportion of housing units covered by NFIP. Recent disasters refer to the number of natural disasters in the 12 years up to and including the given year. House price volatility is calculated as the difference between the maximum and the minimum of a county's real house price index, divided by the value of the index in 1990 or when first available. The geographical concentration of lenders looks at the proportion of the top 5 states' share in the lender's overall lending. When used as a county-level metric, weights are each lender's loan amounts originated. The county-level owner-occupied property/Latino/African American variables look at the proportion of loans backed by such a property/with such a borrower. Delta within variables' names indicates first differences. Specification 1 and 2 are based on overall risk categories – including heat, flood and drought while specifications 3 and 4 are based on flood risk only. Specification 1 and 3 (2 and 4) refer to counties with high (low) climate change indicators as per the three-class standard deviation method using 1.5 (-1.5) standard deviation as the cut-off. Driscoll-Kraay standard errors are used. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

6.6. Conclusions from the case study

One way in which residential mortgage lenders could reduce their exposure to the changing climate is by selling the climate-riskiest loans to GSEs. I find that in tandem with growing climate change awareness in the past few years, loans that are most exposed to the changing climate – measured as the expected increase in the number of extremely hot days, drought days or flood risk days in the county – have increasingly been sold on to GSEs. The increase is particularly marked from 2016 – when granular climate change projections became widely available. I observe the relationship at both independent mortgage companies and banks. Results appear to reflect lenders' desire to reduce risk exposure in areas expected to be most exposed to the changing climate. Indeed, it is only in these areas that I observe GSE securitisation rates to be inversely related to the extent of flood insurance coverage, suggesting one may act as a substitute for the other.

My study adds to the literature in a number of ways. First, results show that lenders are reacting to future projections (or expected macroeconomic and housing market repercussions of such), I control for past or contemporaneous macroeconomic, demographic, climate and disaster variables in the multitude of specifications. The focus on future climate projections and residential mortgage lender behaviour is a novel research angle – especially for risks beyond SLR. Such a forward-looking focus is significant in the context of non-linearities and feedback loops preventing future climate change to be seen as simple extensions of the past. Second, the case study considers multiple dimensions of climate change and documents reactions to the combined risk. Thus, it provides broader evidence. Third, it focuses on non-coastal areas which have received considerably less attention by scholars studying the nexus between climate change, housing market and finance.

The evidence presented in this study adds to the growing body of literature documenting adaptation from residential mortgage lenders which, from a financial stability point of view, is a welcome development. Results, however, also draw attention to GSEs’ framework of rules and pricing. In this respect, further studies could build on my results. For example, it would be particularly useful to assess the risk to public finances emanating from GSEs’ climate risk, undertake a holistic analysis including socio-economic impacts of the costs and benefits of supporting housing markets in the climate-riskiest areas, and assess the potential impact if GSEs introduce climate change-related criteria in all aspects of their decision-making process.

7. OVERALL CONCLUSIONS

The linkage between residential mortgage lending and local climate projections beyond sea level rise risk has hitherto received little attention in the scientific climate finance discourse despite recognition of the detrimental effects of extreme heat, drought or flooding on economic output measures. The dissertation makes of number of scientific and policy-relevant contributions.

First, the dissertation furthers the conceptual understanding of the nexus between future climate and lenders' credit risk. Through economic, demographic, physical destruction and policy channels, future climate conditions can affect today's housing market and, thus, the residential mortgage market. While much evidence is available that I draw on to put together the conceptual linkages map, a priori it is not clear whether lenders do, indeed, consider climate risk in their lending decisions.

Second, to address the aforementioned research gap, the dissertation presents evidence on how climate change is shaping the US residential mortgage market. An important conclusion is that some reaction from mortgage lenders is observable. I document that loans are slightly more expensive and loan terms shorter in areas most exposed to increases in heatwaves. Comparing an area with no projected increase in the number of hot days with an area for which the average of 32 days' rise is projected, suggests this effect alone corresponds to a 2 basis points difference in the rate spread. 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). Another way in which lenders are mitigating their risk is by selling their climate-riskiest loans to government-sponsored enterprises which largely ignore climate change risks in their framework. From 2016 to 2019 the proportion of loans sold to GSEs in high climate change indicator counties (expressed as a fraction of the county's 2007-2012 average) exceeded those in their synthetic control county by 10-16 percentage points. The offloading of the risk to GSEs has in fact intensified in the more recent years of the study (2016-2019). The evidence thus points to increasingly mitigated climate risks at lenders in the more recent past – which is not at odds with the documented increase in public awareness of climate change in the US (Howe et al. 2015). Importantly, these results are gained through large-sample statistical estimations – using linear regressions, panel regressions, matching and difference-in-difference methods. The advantage of large-sample statistical estimations is that it can overcome some of the hurdles of canvassing lenders directly. For example, some of lenders' macroeconomic, demographic and housing market expectations may be shaped by climate prospects indirectly – without 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.

The dissertation 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. Looking at the volume of lending to future heat-prone areas, however, suggests climate change considerations play second fiddle to business rationale. Mortgage volumes in the counties most exposed to future heat reflect the higher concentrations of the country's population and economic output (relative to the land share of these areas). That said, lenders do reject proportionately slightly more mortgage applications in the counties that are expected to be the hottest even after controlling for a number of factors. Subject to the shortcomings of the data, this may be interpreted as high demand pressures in climate-exposed areas resulting in significant lending volumes despite lenders' somewhat reduced appetite to lend.

Third, reviewing results from this dissertation suggests that non-banks are ahead of banks in their reaction to climate change. While both groups offload climate risk to GSEs, the difference-in-difference style treatment effect between the most climate-exposed areas and their (synthetic) counterparts is larger for non-banks than for banks. In addition, it is only non-banks' rather than banks' mortgage rates that reflect extreme heat prospects. One reason for non-banks' more advanced reaction to climate change 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.

The implications of these results are multiple and far-reaching.

At a financial system level, a key question is the extent to which financial markets are incorporating climate risks properly – anticipating risk events and efficiently discounting them. The better markets are at incorporating the risk today, the lower the probability of extreme price movements and bankruptcies in the future. There is widespread belief that financial market participants are still underestimating the risks, leading to financial stability concerns. Approaching the issue from this angle, my results are somewhat reassuring. In aggregate, at least, residential mortgage market participants are reacting to climate change to some extent. That said, given the considerable lending volumes in the climate-riskiest areas as well as common exposure across many residential mortgage lenders to the same climate change dimension, further investigation by financial stability authorities would be useful to ascertain whether the extent of risk incorporation is sufficient. A detailed study of mortgage lending practices with respect to climate change carried out by *bank* supervisors would be particularly beneficial. Although I study US mortgages, implications go beyond the country's borders. This is because of US residential mortgages' key role in financial cycles and cross-border effects.

I document that climate exposure is being sold by banks and non-banks to GSEs. More analysis needs to be undertaken to ascertain who is ultimately backing the risk – is it the taxpayer (if GSEs are left with the risk), households in areas less exposed to climate change (e.g. if GSEs apply the same pricing and terms and conditions irrespective of climate exposure this could amount to cross-subsidisation) or other market participants (e.g. through the use of credit transfers)? If it is the first, it would be useful to assess the risk to public finances emanating from GSEs' climate risk. A potential cross-subsidisation from less exposed areas raises the issue of environmental sustainability as human presence may aggravate climate change or exposure to climate risk (e.g. through the use of air conditioners or on account of land subsidence caused by buildings). If other market participants are stepping in, it may be worth further exploring associated financial stability implications.

The housing and mortgage markets are important to the real economy. Turbulence in the former can lead to major macroeconomic disturbances (Leamer, 2007; Dynan, 2012). Housing construction and transaction activities create economic output and generate employment in the construction, real estate, banking and legal sectors. The volatility of total output is influenced disproportionately by the volatility in the construction sector (Miles 2015). The 2007-2008 crisis serves as a good reminder of how house values and mortgage defaults can be at the very heart of the problem, weighing on confidence and broader credit conditions, and ultimately affecting income and employment. I find some mitigation of lenders' climate change risk. Economic models incorporating the financial stability implications of residential mortgage lenders' climate change exposure could be informative in deciding whether current levels of mitigation are enough. Such modelling could be particularly useful when thinking at a system level about how best to manage climate risk in residential mortgage lending – from a macroeconomic perspective how should we think about climate exposure transferred to GSEs or long term investors, for example?

Finally, results give some urgency to considerations on how to manage the social impact of changing conditions in housing financing in the most climate-exposed areas. GSE policies could form part of the strategy. The evidence in this paper points to mortgage lenders having changed (at least some) terms and conditions and mortgages becoming more expensive. Over time, such terms and conditions may tighten further and, reflecting varying lender responses, fewer housing finance options may be available until potentially no mortgage finance is offered in the area. Such a process would affect the transferability of the property and some parts of the population may find themselves with stranded assets. 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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