Doctoral School of Business and Management

THESIS SYNOPSIS

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CLIMATE CHANGE AND RESIDENTIAL MORTGAGE LENDERS

PhD dissertation

Supervisor:

Ádám Banai, PhD

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Institute of Finance

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Research background and motivation

The global climate is warming, the number of days with extreme temperatures is increasing, and precipitation patterns are changing dramatically. These changes impact all aspects of life, including financial systems. The dissertation focuses on mortgage lenders' reaction to climate change. There are a number of reasons why understanding how mortgage markets factor in climate change is particularly crucial.

Impact on financial stability and credit to the real economy: US mortgages play a 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). Evidence suggests that US real estate has yet to fully price in climate change (Murfin & Spiegel, 2020). Brisk reassessments of the risk – for example due to natural disasters – may result in house price falls and an increase in non-performing loans. A number of lenders could simultaneously experience hardships, and losses at one firm can spread through both counterparty effects and market valuations of assets. Failure to properly account for such risks raises the probability of disorderly movements in financial markets, and of marked changes in credit provision.

Informing social inequality discussions: Financing conditions that incorporate local climate prospects can affect social inequality. Climate change impacts are often more severe on disadvantaged populations, who may reside in highly exposed areas. Changes in housing finance opportunities may contribute to climate gentrification, displacing or entrenching vulnerable populations.

Policy and risk sharing implications: One risk mitigation technique for lenders involves securitisation to government-sponsored entreprises (GSEs). The transfer of climate risk to GSEs is of policy interest, especially if taxpayer-backed or involving cross-subsidisation between low and high climate risk areas. Such risk sharing could lead to suboptimal incentives, like encouraging construction in flood-prone areas.

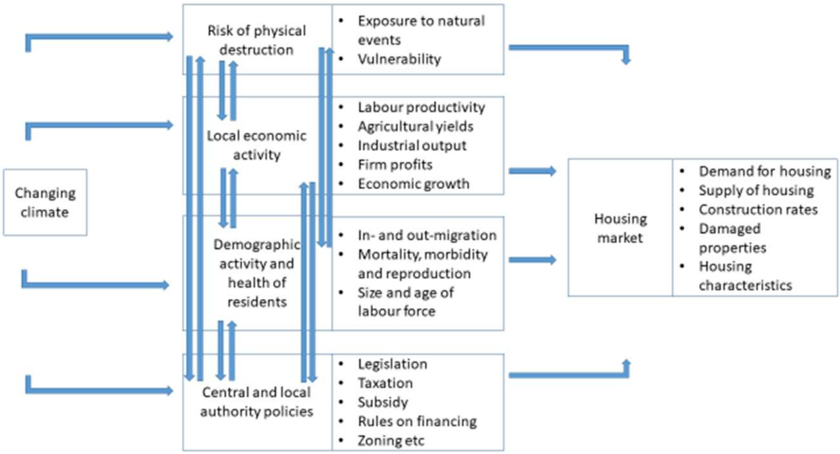
Impact on climate change: Through financing activities, the financial sector has an indirect influence on climate change. Current practices show shortcomings in ensuring that financed properties match future climate conditions, highlighting the need for lenders to consider environmental impact in their decisions.

Research scarcity and practical importance: Despite its significance, research on residential mortgage lenders' reactions to climate change is scarce. Existing studies often focus on the impact of natural disasters or extreme weather rather than long-term scientific projections. The dissertation fills the gap by linking future climate change projections directly to current lender behavior.

Conceptual underpinnings

Climate change can affect lenders through changes in house prices, borrower behaviour, and local economic conditions. For example, extreme heat can lead to physical destruction, lower labor supply, reduced economic growth, and increased health issues – with an effect on the probability of default (PD) and the loss given default (LGD) of mortgages.

Figure 1 Climate change and the housing market: channels and interactions



Source: Author

Existing research on climate change and lender behaviour

Despite limited research on lenders' reactions to climate change, some recent studies have begun to explore how lender behaviour changes when climate risks become evident due to events like natural disasters or abnormal weather. These studies yield mixed results: Garbarino and Guin (2021) found that severe floods in England did not lead to decreased property valuations or altered mortgage terms, while Cortés and Strahan (2017) observed increased US mortgage lending in disaster-affected areas. Ouazad and Kahn (2019) noted that following disasters, the option value of government-sponsored enterprise (GSE) securitization increased, with more risky loans bunching just below GSE limits. Duan and Li (2019) showed that high temperatures reduce mortgage approvals and loan amounts, particularly in areas with strong climate change beliefs or high sea level rise risk. These studies indicate complex lender responses influenced by local conditions and perceptions, underscoring the need for future research that directly links climate projections to lender behavior, as current projections suggest significant variability in future climate impacts.

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 to all forms of climate phenomena. Instead, through case studies I present evidence on: overall lending amounts, rejection rates, interest rates, loan term and securitisation to GSEs. I mostly study heatwaves (extreme heat) but also flood risk and drought risk. Sea level rise risk is beyond the scope of the dissertation.

Methodology and datasets used

For climate change projections I use data from the Applied Climate Information System (ACIS). The data are a US downscaled version of global climate models (CMIP5) – which feature in the UN's Intergovernmental Panel on Climate Change (IPCC) reports – and have first become available in the second half of 2016 (USGS, 2016). Unless otherwise stated, I use the medium carbon emission scenario (RCP4.5).

For loan-level mortgage data, I turn to HMDA which was created by Congress and is the most comprehensive publicly available database for US mortgages. Banks and non-bank financial institutions must report to HMDA if they have significant assets and meet specific criteria. Similar to Keenan and Bradt (2020), my research focuses on "vanilla mortgages," which are conventional loans secured by first lien, single-family homes (up to 4 units), not manufactured, intended for home purchase, and originated loans. Other datasources are included in the table below.

Table 1. Other datasets and sources

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

I apply the following main methodologies – more in the full dissertation.

Loan denials rates

In Case study 1 I construct loan denials rates. The simple denials rate is the ratio of denied loan applications to the sum of originated loans and denied loan applications (Duan and Li, 2019). To calculate the sophisticated denials index, based on Keys and Mulder (2020), I use the following equation 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. Following Keys and Mulder (2020), a lender is considered local if it originates 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.

Interest rates and loan terms

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. 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) based on Hurst et al. (2016), and for competition amongst lenders and local housing market risks – measured via the house price volatility – based on Feng (2018). I apply heteroskedasticity-consistent standard errors clustered at a county level and I include a dummy for each lender.

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 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).

As a robustness check, I follow the IV/2SLS approach as applied by Ambrose et al. (2018).

Risk transfer to GSEs

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 local news coverage of climate risk grew (Keys & Mulder, 2020). 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.

For each individual risk category $r \in$ {drought, flood, heat} and county i :

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

Where δ represents the projected increase in the number of hot/wet/dry days per annum, 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 (CCI) of high, medium and low. Thresholds for drought, flood and hot days are consistent with those in NOAA’s Climate Explorer website.

For each high CCI county I assign a low CCI counterpart using the synthetic control method. The purpose of this matching is to 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, and in which county securitisation trends would have followed a similar pattern had it not been for the fact that one is a high CCI 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).

First, for each high CCI county I identify a donor pool consisting of the 150 low CCI counties with 2007-2012 average securitisation rates closest to the high CCI county.

Then I seek to find weights to minimise the difference beteen the high CCI county and its synthetically created counterpart. 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. 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 each year. Then, similar to Keys and Mulder (2020), I calculate difference-in-difference style treatment effects for each year, comparing each county to its 2007-2012 average to adjust for pre-existing differences in GSE levels across counties. Repeating this process for each high CCI county allows the calculation of the cross-county average treatment effect.

To calculate confidence intervals I follow Keys and Mulder (2020) and Cavallo et al. (2013). For each *low* CCI county I create a synthetic control county using the same process as above (from other low CCI counties). I then calculate treatment effects for each year for each low CCI county. 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 high CCI counties. The confidence intervals show us where the average placebo effect is each year with a 95% probability.

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. In nearest neighbour matching I find a counterpart from existing low CCI counties that is as similar as possible to the high climate change county.

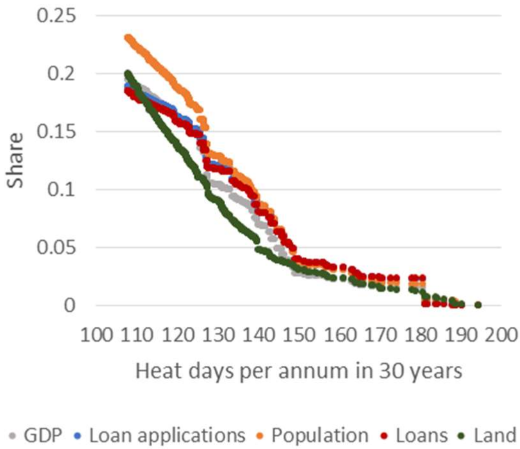
Main results of the dissertation

Case study 1 Overall Conclusion: The mortgage share of areas exposed to future heatwaves 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 it is not a greater lending appetite that is behind the higher lending volumes.

1.1. How does the volume of mortgages originated in the US counties that are most vulnerable to future heat waves, compare to such counties' share of land area, economic importance and population?

In the areas most exposed to future heatwaves, the share of loans exceeds the land share of these counties, but is not out of line with the share of economic activity or population (Figure 2). This is because heat-prone areas account for comparatively greater economic activity and higher populations. I reach the same conclusion regardless of how I measure exposure: i) the change in heat days over the next three decades or ii) the level of future heat.

Figure 2. Mortgage lending in the area as a function of the number of "hot" days expected in 30 years



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

1.2. What do we know about supply and demand effects in lending patterns?

Looking at simple and sophisticated denial rates suggests 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. The sophisticated denials index, which attempts to filter out regional differences in the characteristics of loan applications, confirms that slightly more loan applications are denied in the counties most exposed to temperature change, looking at both future levels (Table 2) and changes (included in the dissertation). 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 – having controlled for other factors.

Table 2. 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

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). 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.

Case study 2 Overall Conclusion: 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. It is lending from non-banks, rather than banks, that appears sensitive to the changing climate.

2.1. Are interest rates higher and loan terms shorter in areas that are more exposed to climate change, controlling for other variables?

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). 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 (threshold of 90°F or 95°F: Specifications 1 and 3) and the emission scenario (medium or high: Specification 1 and 2).

Table 3. Baseline regression results of climate projections on the rate spread

	(1)	(2)	(3)	(4)
Change in Hot days by2048 Medium emission, °90F (days)	.0578**			.0722***
	(.0287)			(.0234)
Change in Hot days by2048 High emission, °90F (days)		.0501**		
		(.0234)		
Change in Hot days by2048 Medium emission, °95F (days)			.096***	
			(.0248)	
Extreme no hot days dummy				8.3784***
				(2.1632)
Controls	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 first three climate variables are defined as the projected increase in the number of days with maximum temperatures above the threshold, 2048 compared with the 2003-2012 average. The extreme number of hot days dummy is defined as the top 1 per cent of counties in 2048 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 ommitted 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 4 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 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).

Table 4. Probit regression results: probability that term of loan < 30 years

	Loan term < 30 years		
	Coeff.	St. Error	Sign.
Change in Hot days by2048 Medium emission, °90F (days)	.00580	.00043	***
Extreme no of hot days dummy	.17994	.02622	***
Controls	Yes, see notes		
Observations	1981643		
McFadden's Pseudo R2	0.1869		
Lender dummies	Yes		

Notes: The first climate variable measures the projected increase in the number of days with maximum temperatures above 90°F, 2048 compared with the 2003-2012 average. The extreme number of hot days dummy is defined as the top 1 per cent of counties in 2048 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 ommitted from the table for presentational purposes. Heteroskedasticity-consistent standard errors in parentheses are clustered at county-level. *** p<.01, ** p<.05, * p<.1.

2.2. Do we see additional concerns reflected in mortgage characteristics at the extremes of projected levels of hot days?

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 (Table 3, specification 4).

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 (extreme) climate variable is (also) highly statistically significant. Directionally linear regressions with OLS estimation yield similar results.

2.3. Do climate change concerns appear more pronounced in the mortgage rates of certain lenders?

Non-banks, in general, apply lower interest rates in my sample than banks (Table 5). 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-bank rate spreads are, however, 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 5. Regression: the impact of non-bank lenders and climate projections on the rate spread

	Coef.	St.Err.	Sig
Change in Hot days (days)	.0069	.0319	
Change in Hot days (days)* 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 first climate variable measures the projected increase in the number of days with maximum temperatures above 90°F, 2048 compared with the 2003-2012 average. Extreme number of hot days dummy is 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 ommitted 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.

Case study 3 Overall Conclusion: 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.

3.1. Are GSE onselling rates higher in areas most exposed to climate change?

I define GSE onselling rates as the proportion of originated mortgages under GSEs' conforming limit sold on to GSEs. The baseline specification shows that in recent years GSE securitisation rates in high CCI counties exceeded those in their synthetic control county, (controlling for other factors) (Figure 3).

Figure 3. Synthetic control with overall climate change indicator and an extreme (1.5 SD) cut-off

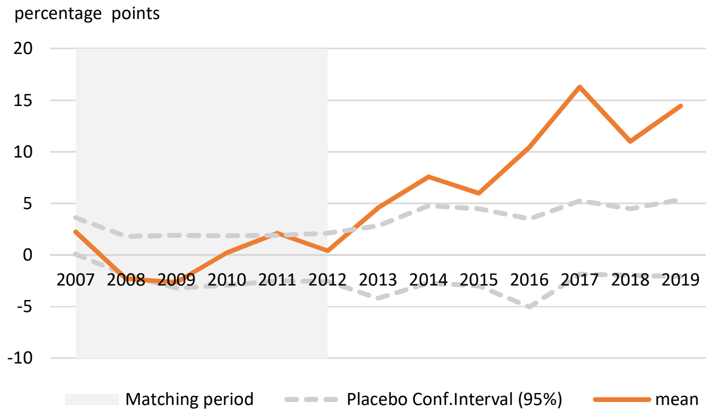


Figure 3 summarizes the treatment effect on GSE rates from the synthetic control method using the overall climate change indicator – which includes heat, flood and drought risk. High (low) climate change indicator (CCI) counties are defined using a three-class standard deviation method using 1.5 (-1.5) standard deviation as the cut-off. Synthetic matches have been performed on 13 variables. 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.

3.2. Has this relationship changed in the past few years?

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 high CCI counties (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 the two-sided 95% interval of placebo treatment effects, suggesting statistical significance.

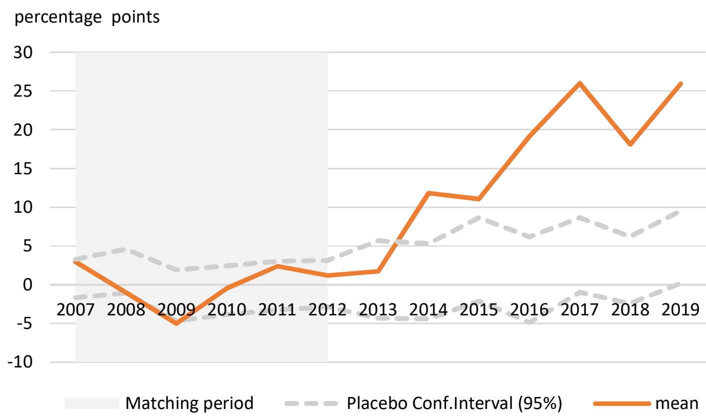
3.3. Is there evidence of firm heterogeneities in GSE on-selling activity with respect to climate change exposure?

Fuster et al. (2019) show that in recent years the number and market share of non-banks have increased significantly. Compared to other lenders, non-bank fintechs, in particular, appear to rely on different information (Buchak et al., 2018 and Seru, 2019). 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.

Results suggest that GSE rates are higher in high CCI counties compared to low CCI counties, controlling for a range of factors, in respect of both banks' and independent mortgage companies' lending (Figure 4).

Figure 4. Synthetic control: banks and independent mortgage companies

Panel A: Banks



Panel B: Independent mortgage companies

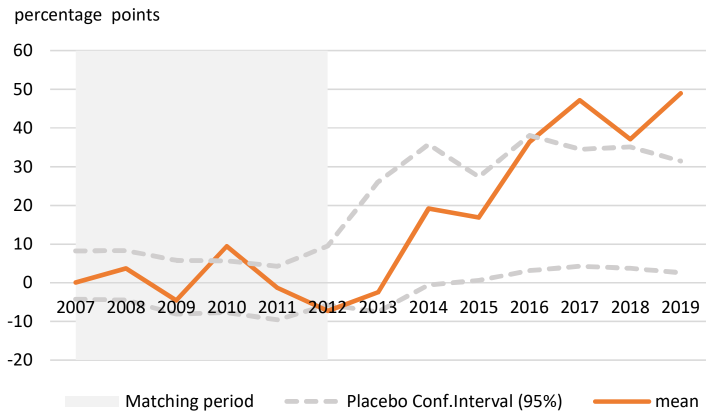


Figure 4 summarizes the treatment effect on GSE rates from the synthetic control method using the overall climate change indicator – which includes heat, flood and drought risk. High (low) climate change indicator (CCI) counties are defined using a three-class standard deviation method using 1.5 (-1.5) 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.

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