Climate Change Concerns and Mortgage Lending[*]

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Abstract

We examine whether beliefs about climate change affect loan officers' mortgage lending decisions. We show that abnormally high local temperature leads to elevated attention to and belief in climate change in a region. Loan officers approve fewer mortgage applications and originate lower amounts of loans in abnormally warm weather. This effect is stronger among counties heavily exposed to the risk of sea-level rise, during periods of heightened public attention to climate change, and for loans originated by small lenders. Additional tests suggest that the negative relation between temperature and approval rate is not fully explained by changes in local economic conditions and demand for mortgage credit, or deteriorating quality of loan applicants. By contrast, Fintech lenders partially fill the gap in demand left by traditional lenders when local temperature is abnormally high.

Keywords: Climate Change, Global Warming, Mortgage Lending, Temperature Anomaly
JEL Classification: G40, G41, Q54

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Abstract

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"What will happen to the 30-year mortgage – a key building block of finance – if lenders can't estimate the impact of climate risk over such a long timeline, and if there is no viable market for flood or fire insurance in impacted areas?"

— Larry Fink, CEO of BlackRock, 2020 letter to CEOs

1. Introduction

As global average temperatures are predicted to rise by the end of this century, many scholars and policymakers have warned of the potential for dramatic damage to the global economy. Predictions of average temperature changes and the economic costs of climate change are uncertain, but generally bleak: for increases of 5–6 °C, which is a "Business as Usual" scenario, the predicted economic loss is 5 to 10% of GDP globally by 2100 (Stern, 2007; Hsiang et al., 2017). A large literature in economics and climate science has documented the adverse impacts of climate change on economic activities, ranging from agricultural yields to industrial output and regional economic growth.

Recently, a burgeoning literature emerged to explore whether financial markets can anticipate and price the risks associated with climate change.[1] Answering this question is important because of the key role that financial markets can play in alleviating the climate disaster: pricing climate risks properly today reduces the possibility of wealth transfers between uninformed and sophisticated agents, and reduces the likelihood of extreme price movements in the future. Indeed, policymakers and investors worldwide have expressed concerns about the extent to which climate risks could affect financial stability.[2] The bankruptcy of PG&E after the 2018 California wildfires is a recent example of how investors are still drastically underestimating the risk that climate change poses to companies' bottom line[3].

[1] See Bansal, Kiku, and Ochoa (2016), Baldauf, Garlappi and Yannelis (2020), Bernstein, Gustafson and Lewis (2019), Giglio, Maggiori, Rao, Stroebel and Weber (2021), Painter (2020), and Hong, Li and Xu (2019) for more details.

[2] Most notably, Mark Carney, the former head of the Bank of England, recently linked these risks to financial stability (Carney, 2015). A coalition of 39 central banks, representing about half the global economy, including the central banks of England, China, Canada Japan and the European Union (but not the United States), has convened a working group to study the effects of climate change on financial markets.

[3] See, e.g., "PG&E: The First Climate-Change Bankruptcy, Probably Not the Last," *Wall Street Journal*, Jan. 18, 2019, "Pacific Gas and Electric is a company that was just bankrupted by climate change. It won't be the last." *The Washington Post*, Jan. 30, 2019.

In this paper, we examine whether mortgage lenders account for climate change risks when originating mortgages. Several features of the residential mortgage market make it particularly relevant for studying the pricing of climate risks. First, mortgage is usually collateralized by residential properties, a type of asset that is particularly vulnerable to the impacts of physical climate risks, including sea-level rise and more frequent extreme weather events.[4] Second, most mortgage loans in the U.S. have maturities as long as 30 years, a horizon over which climate risks may well materialize.[5,6] Third, while firms can adapt to the adverse impact of climate change through geographic relocation and/or product diversification (Li et al, 2020), there is no easy way for real estate to adapt to such risks due to its immobility.[7] Fourth, previous studies show that mortgage applications are subject to the discretionary approval by local loan officers (Tzioumis and Gee, 2013; Cortes, Duchin, and Sosyura, 2016), whose perceptions about climate change may affect their lending decisions. Finally, mortgage is an important part of household debt, adding to its relevance in the overall economy.

The potential risks that climate change poses on mortgage loans do not go unnoticed by policymakers and institutional investors. For example, a recent report from Freddie Mac highlights that "*It is less likely that borrowers will continue to make mortgage payments if their homes are literally underwater. As a result, lenders, servicers and mortgage insurers are likely to suffer large*

[4] Hauer et al. (2016) find that a 1.8-meter SLR would inundate areas currently home to 6 million Americans and work by Zillow suggests that nearly one trillion dollars of coastal residential real estate is at risk (Rao, 2017).
[5] For example, Krueger, Sautner and Starks (2019) conduct a survey on investors' views on the horizons over which they expect climate risks to materialize financially. Around 90% believe that physical climate risks will materialize within ten years and 34% state that physical climate risks have already started to materialize.
[6] Based on 2000-2016 Fannie Mae and Freddie Mac Single-Family Loan-Level Datasets, 79% of the originated mortgages have loan terms equal to or longer than 20 years.
[7] In the U.S., mortgage applicants are required to buy flood insurance if the property is in the Special Flood Hazard Area. As a result, one may argue that climate risks are mostly borne by insurance companies. However, various reasons suggest that in reality mortgage lenders may still be exposed to climate risks. First, Kousky (2018) finds both the number of NFIP (National Flood Insurance Program) flood insurance policies and their total dollar amounts have declined substantially since 2006. With the future of flood insurance in doubt, climate change may lead to potentially significant losses for mortgage lenders. Second, policyholders may not maintain their flood insurance over time. A study of NFIP policies between 2001 and 2009 found that the median tenure was only two to four years (Michel-Kerjan et al., 2012). In addition, climate change may impose risks on houses located in areas that are normally considered safe. For example, in Hurricane Harvey's federally declared disaster areas, 80% of the homes had no flood insurance, because they were not normally prone to flooding. To further address this concern, we conduct a robustness test by excluding from our sample five states (California, Florida, Louisiana, New Jersey, and Texas) that jointly account for nearly 70% of NFIP policies and find similar results.

losses.'[8] Glenn Rudebusch, a senior policy advisor for the San Francisco Fed, wrote that "*financial firms with limited carbon emissions could still face substantial credit risk exposure through loans to affected businesses or mortgages on coastal real estate*." (Rudebusch, 2019). Several newspaper articles warn that "*a foreclosure crisis caused by climate change is becoming a real threat to the mortgage industry as extreme storms and other natural disasters increasingly occur in places where borrowers might not have flood or fire insurance*."[9]

To operationalize the idea, we need a proxy that correlates with public belief about climate change over time and across regions. Following a large literature in climate science, we use the local temperature variation to proxy for public perception of the occurrence and seriousness of global warming. The idea is that although local weather fluctuations may not be *scientifically* informative about the global warming trend[10], public beliefs about climate change do increase significantly after people personally experience unusually warm weather.[11] The psychological foundation of this "local warming" effect could be attribute substitution, whereby individuals use less relevant but available information (for example, local temperature abnormalities) in place of more diagnostic but less accessible information (for example, the global temperature trend) when making judgements. It is also possible that more extreme temperatures lead to more discussions of global warming in the local media, which in turn influence residents' climate change beliefs.[12] An additional advantage of using temperature anomaly is that it is plausibly exogenous to the local economic conditions and thus facilitates causal inferences (Dell, Jones, and Olken, 2014).

We use the monthly temperature data provided by the National Oceanic and Atmospheric Association (NOAA) from more than 10,000 weather stations across the U.S. to construct a baseline

[8] See, e.g., "Life's a Beach", *Freddie Mac*, April 26, 2016.
[9] See, e.g., "The mortgage industry isn't ready for a foreclosure crisis created by climate change," *CNBC*, Jan. 17, 2019, and "Climate change could cause a new mortgage default crisis," *Financial Times*, Sep. 26, 2019.
[10] We verify the assumption that local abnormal temperatures are largely idiosyncratic and not informative about global warming trend by showing that local temperature anomalies are not persistent.
[11] See, e.g., Li, Johnson and Zaval (2011), Howe et al. (2012), Myers et al. (2012), Zaval et al. (2014), and Konisky, Hughes and Kaylor (2016).
[12] Shanahan and Good (2000) find that climate issues were more likely to be covered in the *New York Times* during periods of unusually high temperatures.

climatic variable. Specifically, the temperature anomaly in a region is the difference between monthly temperature (in Fahrenheit degrees) and the historical average temperature (from 1961-1990) in the region. We then take a 36-month moving average of this temperature anomaly as our main variable of interest. [13] Using this temperature anomaly measure, we first verify that abnormally high local temperatures over the past 3 years lead to elevated attention to climate change and heightened climate change beliefs in that region. We measure attention using the Google Search Volume Index (SVI) for the topic "Global Warming". Our measure of local climate change belief is from the Yale Climate Opinion Maps (Howe et al., 2015).[14] The resulting effect is non-linear, as attention to global warming and belief in climate change spike only when local temperature is in the warmest quintiles.

We next examine whether the effect of unusually warm weather extends beyond influencing climate change beliefs and has any impact on agents' real decision-making. We use mortgage origination as a laboratory to examine this question, as mortgage applications are subject to discretionary approval by local loan officers, whose belief about climate change may affect their lending decisions.[15] Our null hypothesis is that local temperature fluctuations will not affect mortgage origination if lenders consider climate risks as irrelevant for mortgages, or if they cannot connect higher local temperature to a larger narrative of climate change. The alternative hypothesis is that experiencing abnormally high temperatures make lenders more concerned about climate change and its potential negative impacts on local housing market. As a result, mortgage lenders may curtail exposure to regions experiencing abnormally high temperatures, by approving fewer mortgage applications, originating a lower amount of loans, or charging a higher interest rate on loans.

[13] A positive (negative) temperature anomaly means that the 36-month average temperature in a region is warmer (cooler) than the historical average temperature in the same region (from 1961- 1990).

[14] Specifically, we use the percentage of population who are somewhat/very worried about global warming and who think global warming will start to harm people in the United States now/within 10 years in a county as the measure of local climate change beliefs.

[15] We conduct two tests to substantiate this claim that mortgage approval decisions are made locally (Cortes, Duchin, and Sosyura, 2016). First, we test whether the effect of temperature anomaly on loan origination is stronger for smaller lenders which are more likely to have discretionary approval decisions. Second, we conduct a within-lender analysis by comparing the loan origination decision of the same lender in two different counties with exposure to different temperatures.

Using detailed mortgage applications data collected under the Home Mortgage Disclosure Act (HMDA) over the period from 1990 to 2016, we document a strong negative effect of local temperature anomalies on mortgage origination at the U.S. County level. Our empirical specification controls for county and state by year fixed effects, thus the temperature effects are identified from the county-specific deviations in temperature from the county averages after adjusting for shocks common to all counties in a state (Deschenes and Greenstone, 2007). Our baseline result shows that a 1°F increase in the past 36-month average temperature anomaly in a county reduces the mortgage approval rate by about 0.88 percentage points in the same county, which represents 10.7% of the within-county standard deviation of the loan approval rate in our sample, indicating not only a statistically significant, but also economically important effect. Looking into the reasons for loan denials, we find the lower approval rate is mainly due to "collateral" reason, and not related to other reasons. This evidence further buttresses our argument that the lower loan approval rate is likely attributed to lenders' rising concern about potential collateral damage brought by future climate change.

We find an even more striking effect of local temperature anomalies on the amount of loans originated. A 1°F increase in the local temperature anomaly in a county leads to an approximately 6.7% lower amount of loans originated. In dollar terms, this translates into a $1.26 million reduction in loan amount for a median county-year. In contrast, we find an insignificant effect of temperature anomaly on loan interest rate.[16] When we break the temperature anomaly into quintile ranks, we find that the negative impact is concentrated in the top quintiles when unusually warm weather takes place. The negative effects of temperature anomaly on loan origination are robust after we exclude subprime mortgage crisis period (year 2006 to 2010) from the sample, control for damages caused by natural disasters at county-year level, and further account for the National Flood Insurance Program. We also conduct placebo test by randomly assigning counties to high temperature anomaly group and find the

[16] The insignificant effect on interest rate is consistent with the prior literature that loan pricing is determined mainly by computerized bank algorithms that rely on hard information, such as the borrower's FICO score, loan-to-value ratio, and documentation level, with relatively little input from the loan officer (Rajan, Seru, and Vig, 2015).

actual coefficient estimate falls in the extreme left tail of the distribution of the placebo estimates. This suggests that the effect we document is unlikely caused by serial correlation in temperature anomaly.

Temperature shocks could affect mortgage origination through either the credit demand or the supply channel. On the demand side, studies document that higher temperatures negatively affect labor productivity (Zivin and Neidell, 2014), agricultural yields (Schlenker and Roberts, 2009), industrial output (Jones and Olken, 2010), health and mortality (Deschenes and Greenstone, 2011), firm profits (Addoum, Ng, and Ortiz-Bobea, 2023), and economic growth (Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015). The deteriorating local economic conditions could drive firms to relocate and residents to migrate to less affected areas, resulting in a reduction in local employment opportunities and tax revenues, and undermine the local governments' ability to maintain proper infrastructure and public services. As a result, the demand for mortgage credit could be negatively affected by a warming local temperature, even though the lenders' willingness to supply credit has not changed.

Our empirical design helps disentangle the two channels. First, we use state by year fixed effects to account for time-varying local economic conditions, which may affect local residents' demand for mortgage credit. We also include county-level macroeconomic variables such as employment growth, wage growth, population growth, and housing price index to control for county-level economic conditions. Second, we find a significant effect of temperature anomaly on loan approval rate. Conceptually, the loan approval rate is the ratio of the number of loan applications approved to the number of loan applications reviewed in a county-year. This makes it a relatively clean measure of lenders' willingness to supply mortgage credit conditional on the demand for mortgage. Third, we re-run our test on a subsample of counties that have experienced a strong growth in demand for mortgage credit, as measured by an above average growth in the number of applicants and the amount of loans applied.[17] We continue to find a negative effect of temperature anomaly on mortgage origination in this subsample. Fourth, we use natural disasters hitting neighboring counties as an alternative shock to lenders' climate change perception (Alok et al., 2020; Correa et al., 2021). The idea is that lenders' concern about climate change should intensify after observing climate change-related natural disasters in neighboring counties, but these disasters should have no direct impact on the county's economic conditions. We find a similarly negative effect of these indirect natural disasters on the mortgage origination of counties, which are themselves not affected by disasters. These additional tests suggest that the effect we document unlikely operates *solely* through the credit demand channel.

Still, one may be concerned that the quality of mortgage applicants may deteriorate in counties experiencing high temperatures due to out-migration, which could then affect loan approval decision of lenders through the default risk channel.[18] To address this concern, we first conduct a falsification test using the sample of Fintech mortgage lenders. The idea is that, for Fintech lenders, the application and review process for mortgages are almost entirely conducted online, and no human loan officers are involved in the decision-making process (Fuster et al., 2019). As a result, if abnormal temperatures affect mortgage lending through affecting loan officers' climate change belief, we should find an insignificant effect on loans originated by Fintech lenders, or even a positive effect if they can adjust supply more elastically (Fuster et al., 2019). On the other hand, if the effect we document is due to greater mortgage default risk in areas experiencing abnormally high temperatures, we should find a similarly negative effect for loans originated by Fintech lenders. Our results show a weak positive effect of temperature anomaly on loans originated by Fintech lenders. This finding is inconsistent with

[17] The idea is that since the demand for mortgage credit is high in this subsample, the reduction effect of temperature anomaly on mortgage lending is more likely to operate through the credit supply channel.
[18] We find that abnormally high temperature indeed affects the quality of loan applications, and counties experiencing abnormally high temperatures have lower quality mortgage applicants, as measured by higher loan-to-income ratios and lower income levels. For this reason, we control for these characteristics of mortgage applicants in the baseline regression.

the default risk channel, and instead suggests that Fintech lenders (partially) fill the credit gap left by traditional lenders.

Furthermore, we conduct a granular analysis at the lender-county-year level and control for county*year fixed effects (and lender*year) fixed effects, which allows us to compare different lenders' mortgage approval decisions in response to abnormally hot temperatures in the same county. We create a dummy variable, *small lender*, that indicates lenders in the lowest quartile based on the number of states operated and interact this indicator with temperature anomaly. We find a significantly negative coefficient on the interaction between small lender and temperature anomaly. Under the assumption that lenders of different size in the same county face the same pool of mortgage applicants (hence the same default risk), the stronger response of smaller lenders to temperature anomaly we document is unlikely driven by the default risk channel.

After documenting the robust effect of local temperature anomalies on mortgage origination, we examine its heterogeneous effects to shed light on the underlying mechanisms. The mechanism we propose is that lenders' perception of climate change increases significantly after they experience unusually warm weather, and they take actions to reduce lending to the local housing market. This "belief updating" mechanism implies that concerns about climate change should more likely induce adaptations in regions that are more heavily exposed to the physical risks of climate change. We test this prediction by conditioning on a county's exposure to the risk of sea-level rise (Hallegatte et al., 2013). Consistent with this conjecture, the coefficient estimates suggest that a 1°F increase in the past 36-month average temperature anomaly in a county exposed to sea-level rise risk reduces the mortgage approval rate by 2.0 percentage points and the loan amount by 21.2%. This effect is about 1.5 times stronger than that on counties less exposed to the risk of sea-level rise.

The "belief updating" mechanism relies on a key assumption that lenders can connect higher local temperature to a larger narrative of global warming. This should be more likely when the public, overall, becomes more aware of climate risks. To provide such evidence, we use a quasi-natural experiment surrounding the release of the Stern Review, which significantly increases the public awareness of climate change (Painter, 2020).[19][20] Using a difference-in-differences design, we indeed find the effect of abnormally high temperature on mortgage lending is much stronger after the release of the Stern Review. Since the release of the Stern Review unlikely changed the likelihood or physical risks of climate change, this result suggests that being aware of climate change is a key determinant of whether agents will take adaptive actions. In a similar vein, we find the negative effect of temperature anomalies on mortgage lending is more pronounced in periods with more intense media coverage on climate change related topics.

Related Literature and Contribution

This paper makes several important contributions to our understanding of the economic impacts of climate change. A large volume of literature in economics and climate science has examined the impact of climate change on various economic outcomes (Dell, Jones, Olken, 2014). At the macro level, Dell, Jones, and Olken (2012) document the effect of a warming of 1°C in a given year reducing the per capita income in a country by 1.4 percentage points, although the effect only manifests in poor countries. However, recent studies show that rising temperatures could negatively affect economic growth in U.S (Colacito, Hoffmann, and Phan, 2019). At the micro level, higher temperature has been documented to negatively affect agricultural yields (Schlenker and Roberts, 2009), labor supply (Zivin and Neidell 2014), labor productivity (Seppanen, Fisk, and Lei, 2006), and firm profitability (Addoum et al., 2023), which serve as the channels through which rising temperature affects aggregate economic growth. One implication of our study is that climate change may also adversely affect the local economy through reducing the supply of mortgage credit in regions most vulnerable to climate risks.

[19] On October 30, 2006, the economist Nicholas Stern published a report detailing the costs of damages that climate change is expected to have on the world economy. The “Stern Review" is one of the earliest and most thorough analyses of the economics of climate change and one of the most well-known. After the release of the Stern Review, it is likely that lenders began paying more attention to the risks that climate change poses on their mortgage loans.

[20] A shocking documentary film, “An Inconvenient Truth”, which was released around the same time (October 2006), may also help raise people’s awareness of global warming.

This paper also adds to the new climate finance literature that examines whether the financial market efficiently prices climate risks (Hong, Karolyi, and Scheinkman, 2020; Giglio, Kelly and Stroebel, 2021). Evidence to date is still mixed. Hong, Li, and Xu (2019) show that global stock markets do not anticipate the effects of predictably worsening droughts on agricultural firms until after they materialize. In contrast, Bansal, Kiku, and Ochoa (2016) find that climate change risk, as measured by temperature rise, has a negative impact on stock market valuation, implying that markets do price climate change risk. In the real estate market, Giglio et al. (2021), Bernstein et al. (2019), and Baldauf et al. (2020) show that home buyers do consider the negative effect of sea-level rise on real estate prices in coastal areas, although Murfin and Spiegel (2020) find no evidence of significant valuation effects. Painter (2020) documents that the municipal bond market prices climate change risks, especially for long-term bonds issued by counties more likely to be affected by sea-level rise. However, he also shows that the market began pricing climate risks only after climate change elicited significant public awareness. The evidence in our paper suggests that lenders do account for climate change risks when originating mortgages, but only when they sufficiently believe in climate change. Consistent with our finding that mortgage lenders care about climate risks, Ouazad and Kahn (2022) find that banks located in areas hit by severe natural disasters reduce their own climate-risk exposure by selling riskier disaster-area mortgages to Fannie Mae and Freddie Mac. A closely related paper by Nguyen et al. (2020) finds that lenders charge higher interest rates for mortgages on properties exposed to a greater risk of sea level rise. Deng et al. (2021) document that areas with high temperature experience an increase in mortgage default, while Issler et al. (2020) find a significant increase in mortgage delinquency and foreclosure after wildfires in California.

Our paper differs from these contemporaneous papers in several important dimensions. First, While Deng et al. (2021) and Issler et al. (2020) focus on the effect of climate change risk on ex-post loan performance, our study highlights the impacts of climate change concerns on lenders' ex-ante lending decision. While lenders' concern about climate change could be impulsive, we show that it still matters with real economic consequence. The effect of climate change perception we document also varies over time within the same location, which is different from the time-invariant effect of sea-level rise exposure studied in Nguyen et al. (2020). Secondly, our focus on the impacts of subjective climate change belief on the quantities of loan originated also complements Nguyen et al. (2020), who focus on the impacts of objective sea-level rise exposure on loan pricing. Previous literature suggests that loan pricing is driven primarily by computerized bank algorithms that rely on hard information, such as the borrower's FICO score, loan-to-value ratio, and documentation level (Rajan, Seru, and Vig, 2015; Cortes, Duchin, and Sosyura, 2016). Another key feature of the loan pricing process is that it is typically centralized at the firm level, and loans are priced with relatively little input from the loan officer. As such, loan pricing is less likely affected by localized shocks to loan officers compared to loan approval decision.

Our study also complements prior works which have studied how local weather conditions influence public beliefs and perceptions about global warming.[21] Myers et al. (2012), Zaval et al. (2014), and Akerlof et al. (2013) show that personal experience with global warming leads to an increased perception of climate risk in the U.S, as elicited in surveys. Howe et al. (2012) document similar findings using international surveys. Li, Johnson, and Zaval (2011) and Lang (2014) find that local weather fluctuations cause people to seek more information about climate change through the Internet. Several recent studies show that the effects of abnormal weather extend beyond online search activities to observable action on environmental issues. Li, Johnson, and Zaval (2011) find that people donate more money to global warming charities after experiencing warmer than usual temperatures. Herrnstadt and Muehlegger (2014) show that members of the U.S. Congress are more likely to take a pro-environment stance on votes when their home state experiences unusual weather. Using international data, Choi, Gao, and Jiang (2020) show that attention to "global warming", as measured

[21] Evidence that individuals tend to extrapolate from recent personal experiences when forming expectations about aggregate outcomes is also found in other contexts such as house price changes and unemployment (Kuchler and Zafar, 2019).

by Google search volumes, increases significantly after a region experiences higher than normal temperature, and this affects investors' trading on carbon-intensive firms. Our finding that concerns about climate change increase significantly after a region experiences abnormally high temperature is consistent with these studies. Relative to these studies, we further show that agents' heightened beliefs about climate change affect their real decision-making. Our study thus sheds light on an important policy question: will the predicted rising temperatures and extreme weather events lead society to reassess climate change risks and invest more resources in mitigation and adaptation?[22]

The rest of the paper is organized as follows. Section 2 provides a conceptual framework linking local temperature variation to climate change belief. Section 3 describes the data and presents summary statistics. Section 4 presents the main empirical findings on the relation between temperature anomalies and mortgage origination. In section 5, we conduct tests to shed light on the underlying mechanism. Section 6 concludes the paper.

2. A Conceptual Framework

In this section, we outline a simple belief updating process based on Bayes' rule to illustrate how local temperature anomalies can affect agents' beliefs about climate change, even if local temperature fluctuations are unlikely to be informative about the trend of global warming. This framework also serves as guidance for our empirical tests.

A Bayesian updater would use Bayes formula to calculate the probability that global warming is happening based on available evidence and her prior belief in global warming ("prior"). Specifically, Bayes formula for updating global warming belief is:

$$\Pr\,(G|E) = \frac{\Pr(E|G)\,\Pr\,(G)}{\Pr(E|G)\,\Pr(G) + \Pr\,(E|NG)(1 - \Pr\,(G)}$$

[22] It seems that attitudes and beliefs in climate change have already started to shift in the U.S. because of more frequent extreme weather events in recent years. See, e.g., "Floods and storms are altering American attitudes to climate change," *The Economists*, May 30, 2019.

where G and NG are states of the world with and without global warming, respectively. Pr(G) is the agent's ex-ante belief about global warming prior to observing the evidence, and E is the observed evidence. In general, the evidence could include national or local weather, news reports on extreme weather events, an influential scientific report like the Stern Review, or long-run global temperature trend. Bayes' rule makes it clear that the extent to which new evidence shifts posterior beliefs about global warming depends on the probability that the observed evidence is generated by the state of world where global warming is happening (Pr(E|G)).[23] The more likely that an observed weather event occurred because of global warming, the greater the shift in belief in favor of global warming.

In our empirical tests, we use Google search volumes on the topic of "global warming" and local climate change beliefs from the Yale Climate Opinion Maps to proxy for local residents' beliefs in global warming. We use local temperature fluctuations as a proxy for new evidence. The relationship between the two should be significant if the public views abnormally high local temperatures as informative about global warming. We further examine whether the effect of weather abnormalities extends beyond online search activities and beliefs to have any impact on agents' decision-making.

It is worthwhile to point out that if agents are fully rational, local weather fluctuations should not affect their beliefs about climate change once we control for time fixed effects. The reason is that fully rational agents should have the same information about weather patterns for every location in the US. After all, weather is public information. When we include time fixed effects that account for national weather patterns, the residual variation in weather is purely local and should not affect beliefs about global warming. Thus, to be able to identify the effect of local temperature on beliefs, agents must be more likely to use local weather fluctuations as evidence for global warming than they are to use national or global weather patterns. There are many good reasons to believe this could be true. First, psychological studies on cognitive bias argue that people suffer from the availability heuristic in decision-making. People using the availability heuristic tend to give greater weight to more salient

[23] One can prove from Bayes' formula that when Pr(E|G)>Pr(E|NG), Pr(G|E) is an increasing function of Pr(E|G).

events when judging the probability of an event occurring[24] (Kahneman and Tversky, 1974). The availability bias predicts that people are more likely to believe global warming when they have personally experienced unusually warm temperatures, which is a more salient event than statistical information on global temperature trends.

In addition to availability bias, another cognitive heuristic, called attribute substitution, may also explain why local temperature shocks could influence global warming attitudes. This bias proposes that individuals use less relevant but more readily available information (for example, local temperature abnormalities) in place of more diagnostic but less accessible information (for example, global climate change patterns) when making judgements. Third, the local warming effect could be due to people's lack of scientific knowledge, causing them to mistakenly believe that long-term climate change and short-term temperature deviations are highly related. Lastly, it is possible that local temperature fluctuations are observed with less noise than national or global weather patterns. In this case, a Bayesian updater will rationally put greater weight on local weather in the belief updating process. Regardless of the underlying mechanisms, local temperature could matter for the formation of climate change beliefs.

Given this framework, we can make the following predictions regarding the relationship between local temperature fluctuations and beliefs about climate change.

Prediction 1: Abnormally high local temperatures in a region should lead to increased concern about climate change among local residents;

Prediction 2: The more extreme the abnormally high temperatures are, the larger the changes in climate change beliefs would be.

Prediction 2 holds because the likelihood that temperature abnormalities are the result of global warming is larger when temperatures are more extreme.

[24] For example, someone who has witnessed a serious plane accident will judge the probability of such an accident to be higher than someone who has never seen one, even if both have identical statistical information.

3. Data and Summary Statistics

3.1 Data

We obtain data from several sources including: (1) National Oceanic and Atmospheric Administration (NOAA); (2) Home Mortgage Disclosure Act (HMDA); (3) Fannie Mae Single-Family Loan Performance Dataset and Freddie Mac Single-Family Loan-Level Dataset; (4) United States Census Bureau; (5) Bureau of Labor Statistics; (6) Federal Housing Finance Agency (FHFA); (7) Google Trends; (8) Yale Climate Opinion Maps.

First, we obtain temperature data from NOAA. The raw temperature data is based on 5 km gridded data from more than 10,000 land-based weather stations. NOAA aggregates the data and provides monthly temperature data at U.S. county-level for 48 contiguous states since the year 1895. Our primary climatic variable is *Temperature anomaly*, defined as the difference between monthly temperature (in Fahrenheit degrees) and the 30-year average temperature (from 1961-1990) in a county. We then take a 36-month moving average of the temperature anomaly as the main explanatory variable. A positive (negative) temperature anomaly means a recent temperature warmer (cooler) than the historical average.

Second, we obtain detailed mortgage applications from HMDA, which is collected annually by the Federal Financial Institutions Examination Council (FFIEC). The database covers all mortgage applications that have been reviewed by qualified financial institutions in the calendar year. A financial institution is required to complete a HMDA register if it has at least one branch office in any metropolitan statistical area and meets certain criteria (i.e., asset size above a specific threshold). HMDA includes the vast majority of home mortgage applications and approved loans in the United States, and provides information such as lender identity, borrower characteristics (e.g., income, loan-to-income, and race), loan characteristics (e.g., loan amount, type, and purpose), property characteristics (e.g., type and geographic location), and the application outcome (e.g., approved, denied, withdrawn, or closed for incompleteness).

Third, we obtain the loan pricing and loan characteristics information from Fannie Mae Single-Family Loan Performance Dataset (Fannie Mae) and Freddie Mac Single-Family Loan-Level Dataset (Freddie Mac). Loans covered by these two datasets are known as conforming loans, which are loans that are equal to or less than the dollar amount established by the conforming-loan limit set by the Federal Housing Finance Agency (FHFA) and meets the funding criteria of Freddie Mac and Fannie Mae. The Fannie Mae and Freddie Mac (F&F) datasets provide origination and performance data for fully amortizing, full documentations, single-family, conforming fixed-rate mortgages (the predominant conforming contract type in the U.S.). The F&F datasets provide detailed information on a range of borrower, property, and loan characteristics at the time of origination, such as loan interest rate, property location (first 3-digit zip code), borrower credit score, loan-to-income ratio, loan-to-value ratio, and loan term.

Fourth, we obtain U.S. county-level macroeconomic variables from the United States Census Bureau and Bureau of Labor Statistics. We obtain the county-level House Price Index (HPI) data, which is a broad measure of the movement of single-family house prices, from the Federal Housing Finance Agency (FHFA).

Fifth, we download from Google Trends the monthly Search Volume Index (SVI) of the topic "Global warming" in each Designated Market Area (DMA) of U.S.[25][26]. This is used to proxy for people's attention to global warming. The sample period for SVI data is from April 2004 to December 2016. We also obtain the annual climate change belief measures at U.S. County level from Yale

[25] Google offers SVI for topics and search terms. We use topics instead of search terms because the former addresses misspellings and searches in different languages, as Google's algorithms can group different searches that have the same meaning under a single topic. In the paper, we report the results using the SVI of "Global warming", because the search traffic for the topic "Climate change" is much lower than that of "Global warming" in the early years. In more recent years, the SVIs of the two topics are highly correlated.

[26] The smallest geographic unit for Google SVI data is the Designated Market Area in the U.S. DMA regions are the geographic areas in the United States used by the Nielsen Company to measure local television viewing. Since some DMA regions do not have search results for the topic of "Global Warming", we are able to obtain the SVI data for 199 out of 210 DMA regions. More information can be found at: https://www.nielsen.com/intl-campaigns/us/dma-maps.html

Climate Opinion Maps (Howe et al., 2015). Their study provides, at the county level, survey evidence on how respondents answer questions including (i) whether they believe that climate change is happening; (ii) whether they believe that climate change is human caused; (iii) whether they believe that there is scientific consensus on whether climate change is happening; and (iv) whether they will be personally affected by climate change. Specifically, we use two measures from the survey to proxy for people's belief about climate change. The first measure, *Worry*, is the fraction of population in a county who are somewhat/very worried about global warming. The second measure, *Timing*, is the fraction of population in a county who think global warming is already harming people in the United States now/within 10 years. The data on climate change belief is available annually from 2014 to 2018.

To construct our main sample, we begin with all HMDA mortgage applications during 1990-2016. We drop applications that were closed for incompleteness, withdrawn by the applicant before a decision was made, and loans sold by the institution. We additionally drop Fintech lenders using the list provided by Buchak et al. (2018).[27] We aggregate the loan applications to county level and match the temperature data and the macroeconomic variables with the HMDA database. Our final sample contains 83,408 county-year observations for 3,105 unique counties in the U.S. between 1990 and 2016.

In addition, we construct the sample containing loan interest rate information following Buchak et al. (2018). Since the location information of originated mortgages in the F&F dataset is at (first 3-digit) zip code level, we aggregate all acquired single-family fixed-interest mortgage to zip code-level, and match temperature data with the F&F database. The F&F sample contains 12,042 zip code-year observations for 709 unique zip code areas in the U.S. between 2000 and 2016.

[27] The mortgage application process for Fintech lenders is very different from traditional lenders. For example, for traditional lenders, mortgage applications are usually reviewed and approved by local loan officers (Tzioumis and Gee, 2013). However, for Fintech lenders, the application and review process for mortgages is almost entirely conducted online, and no human loan officers are involved in the decision-making process (Buchak et al., 2018). The sample of Fintech lenders includes QuickenLoans (from 2000), CashCall (from 2008), Guaranteed Rate (from 2008), Amerisave (from 2008), Homeward (from 2012), Movement (from 2013), and Summit Mortgage (from 2007).

3.2 Summary Statistics

Table 1 Panel A presents the descriptive statistics. For the period of 1990-2016, the average (median) temperature increased by 1.07-Fahrenheit degrees (1.07-Fahrenheit degrees) relative to the average temperature during 1961-1990. The 25th and 75th percentiles of temperature anomaly are 0.89-Fahrenheit degrees and 1.25-Fahrenheit degrees, respectively. This demonstrates that most counties in the U.S. experienced rising temperatures over the last 30 years, consistent with the trend of global warming. We then examine the persistence of local temperature anomalies. We regress the subsequent 36-month average temperature anomalies on its own (non-overlapping) lag, controlling for county- and/or state by year fixed effects[28]. Appendix Table B1 shows that the coefficients on lagged temperature anomalies are insignificantly different from zero, thus verifying our assumption that local abnormal temperatures are largely idiosyncratic and not informative about global warming trends. However, local abnormal temperatures do affect residents' belief about climate change, as we show in section 4.

The mean (median) approval rate of mortgage applications is 0.70 (0.70). The mean (median) loan amount aggregated to county-level is $190.77 million ($18.90 million), when expressed in 2016 dollars. The mean (median) loan-to-income ratio is 1.67 (1.62). The mean (median) income is $63,262 ($58,806). The mean (median) percentage of minority applicants is 0.22 (0.18). Panel A also reports the summary statistics on climate change beliefs, sea-level rise risk, and the Google search volume index on global warming. According to Yale Climate Opinion Maps, on average 48% of the population in a county are somewhat/very worried about global warming, and 39% of population think global warming is already harming people in the United States now/within 10 years. Figures 1a and 1b plot the fraction of adults at county-level who are somewhat/very worried about global warming and who

[28] For example, in the year of 2008, our independent variable is calculated as the average temperature anomalies from 2005 to 2007. The subsequent 36-month average temperature anomalies (the dependent variable) are calculated as average temperature anomalies from 2008 to 2010.

think global warming is already harming people in the United States now/within 10 years in year 2014, respectively.

[Insert Table 1 Here]

[Insert Figure 1a and 1b Here]

Table 1 Panel B reports the summary statistics for the Fannie Mae and Freddie Mac sample over the period of 2000 to 2016. The mean (median) loan interest rate is 5.33% (5.33%). The mean (median) FICO score is 739.29 (740.04). The mean (median) loan-to-value ratio is 73.13% (73.93 %). The mean (median) loan term is 308.33 (308.06) months. The long-horizon nature of mortgage loans makes the impact of climate change particularly relevant for lenders.

4. Empirical Results

In this section, we first verify that local temperature anomaly is a valid proxy of public beliefs about climate change. We then test whether the effect of unusually warm temperature extends beyond climate change beliefs to have any impact on agents' real decision-making, using mortgage origination as a laboratory. We further disentangle the channels of credit demand and supply in driving the effect of temperature anomaly on approval decision. Lastly, we conduct sensitivity checks to ensure the robustness of our main results.

4.1 Temperature Anomaly and Public Attention to and Belief in Climate Change

Using international data, Choi, Gao, and Jiang (2020) show that Google search activity on the topic of "Global warming" in a city increases significantly when the city experienced unusually warm weather. Following their approach, we examine whether abnormal temperature experienced over the recent 36-month in a region leads to elevated attention towards global warming in that region. We use Google search volume index to measure public attention to global warming (Da, Engelberg, and Gao, 2011). Specifically, we define *Abnormal_SVI* as the (seasonally adjusted) log change of Google search volume index (SVI) on the topic of "Global warming" in each Designated Market Area (DMA).

Panel A of Table 2 reports the effect of temperature anomaly on *Abnormal_SVI*. In column (1), the coefficient on the *Temperature anomaly* is positive and significant at 5% level. This suggests that residents' attention to global warming increases after experiencing abnormally high local temperature. The regression specification includes year-month fixed effects, which means that the effect is observed from the geographic variation in a given month. In column (2), we rank all regions into quintiles based on the *Temperature anomaly* in each month, and use temperature anomaly quintile dummies (Q2-Q5) in regression. The coefficients on quintile dummies suggest that the effect of abnormal temperatures on global warming attention is non-linear. The coefficients on quintile 2, 3, and 4 dummies are not significantly different from zero, while the coefficient on quintile 5 dummy is 0.048 and highly significant. This result suggests that attention towards global warming responds most strongly to extremely high temperatures. Overall, our results based on regional variation within U.S. are broadly consistent with the finding of Choi, Gao, and Jiang (2020) in an international sample.

We next test how local temperature variations influence climate change beliefs, where we obtain the local climate change belief measure from Yale Climate Opinion Maps. Panel B of Table 2 reports the results on the effect of temperature anomaly on *Worry* and *Timing*. It shows that both measures of climate change belief are positively affected by local temperature anomalies, and the effect manifests when the temperature anomaly is in top quintiles. The economic magnitude is also non-trivial. A 1°F increase in the past 36-month average temperature anomaly in a county increases the fraction of population who are somewhat/very worried about global warming by 1.17 percentage points, which is about 23% of the sample standard deviation.

[Insert Table 2 Here]

4.2 Temperature Anomaly and Mortgage Lending

We next examine whether the effect of abnormally high temperature extends beyond climate change attention and belief to have any effect on agents' real decision-making. Our null hypothesis is that local temperature fluctuations will not affect mortgage origination if lenders think climate risks are irrelevant for mortgage loans, or they do not connect higher local temperature to a larger narrative of climate change. The alternative hypothesis is that after experiencing abnormally high temperatures, lenders become more worried about climate change and its potential negative impacts on the local housing market. As a result, lenders may reduce credit exposure to regions vulnerable to climate change, by approving fewer mortgage applications, originating lower amount of loans, or charging higher interest rates. To test these predictions, we estimate the following regression specifications:

$$Loan\ Approval\ Rate_{i,s,t} = \beta_0 + \beta_1 TemperatureAnomaly_{i,s,t-1} + Controls_{i,s,t} + \alpha_i + \emptyset_{s,t} + \varepsilon_{i,s,t} \qquad (1a)$$

$$Ln(Loan\ Amount)_{i,s,t} = \beta_0 + \beta_1 TemperatureAnomaly_{i,s,t-1} + Controls_{i,s,t} + \alpha_i + \emptyset_{s,t} + \varepsilon_{i,s,t} \qquad (1b)$$

$$Loan\ Interest\ Rate_{i,s,t} = \beta_0 + \beta_1 TemperatureAnomaly_{i,s,t-1} + Controls_{i,s,t} + \alpha_i + \emptyset_{s,t} + \varepsilon_{i,s,t} \qquad (1c)$$

The dependent variable is *Loan Approval Rate* and *Ln(Loan Amount)* in equation (1a) and (1b), respectively. *Loan Approval Rate* is the number of loan applications approved divided by the number of loan applications reviewed in county *i* of state *s* in year *t*. *Ln(Loan Amount)* is the natural log of the total dollar amount of originated loans that are not sold to other institutions at the end of the year in county *i* of state *s* in year *t*.[29] The dependent variable in equation (1c) is the *Loan Interest Rate*, defined as the average interest rates of the loans at origination in zip code *i* of state *s* in year *t*. The explanatory variable for all three regressions is *Temperature anomaly*, measured as the 36-month moving average of temperature anomaly in county or zip code *i* of state *s* in year *t*-1.

Following the literature (Munnell et al., 1996), we control for several borrower characteristics (i.e., *Loan-to-income*, *Income*, and *Fraction of minority applicants*) and local economic conditions (i.e., *Employment growth*, *Wages growth*, and *Population growth*) that could affect mortgage

[29] We drop the originated loans that are sold to other institutions to take into account the effect of mortgage securitization.

origination. The controls are measured in the same year as the dependent variables. We include county fixed effects α_i to control for the effect of any time-invariant county characteristics. We also include state*year fixed effects $\emptyset_{s,t}$ to control for time-varying economic fundamentals at the state level, which may affect mortgage origination through the credit demand channel. Standard errors are double clustered at the county and year level (Petersen, 2009). All control variables are winsorized at the top and bottom 1% level to mitigate the impact of outliers.

Table 3 Panel A reports the results for the effect of temperature anomaly on loan approval rate. In column (1), we do not include any controls and the estimated coefficient on *Temperature anomaly* is -0.0117, significant at 1% level. In column (2), we add the aforementioned control variables, and coefficient on *Temperature anomaly* slightly decreases to -0.0088, but still highly significant. The economic magnitude is non-trivial. Based on the coefficient estimate in column (2), a 1°F increase in the past 36-month average temperature anomaly in a county reduces the mortgage approval rate by 0.88 percentage points in the same county, which is about 11% of the within-county standard deviation of the loan approval rate in our sample. In column (3), we rank all counties each year into quintiles based on their temperature anomalies and use the quintile-rank variable in the regression. The coefficient on *Temperature anomaly_Quintile* is significantly negative, with an estimated magnitude of -0.0023. In column (4), we show the result using as explanatory variables dummies indicating temperature anomaly quintile ranks (Q2-Q5). The coefficients on these quintile-rank dummies indicate a strong monotonic effect of local temperature abnormalities on mortgage approval rate. The coefficient on *Temperature anomaly_Q5* is -0.0090, implying that a county in its warmest years has a 0.90 percentage point lower mortgage approval rate compared to its coldest years. The effect is considerably smaller for mildly warm temperatures.

To further shed light on the channel, we investigate the reasons for loan denials. The HMDA data contains specific reasons for rejecting loan applications.[30] If lenders are indeed concerned about future climate risks and its potential impacts on housing value, we expect the lower loan approval rate to be mainly driven by "collateral" reason. To test this, we construct *Loan denial for collateral reason* as the number of loan denials for collateral reason scaled by the total number of loan denials in each county-year.[31] We also construct *Loan denial for other reasons* as the number of loan denials for other reasons (not related to collateral) scaled by the total number of loan denials in each county-year.[32] Table 3 Panel B reports the results for the effect of temperature anomaly on *Loan denial for collateral reason* and *Loan denial for other reasons*. In column (1), the estimated coefficient on *Temperature anomaly* is 0.0069 for *Loan denial for collateral reason*, significant at 5% level. The estimated coefficient implies that a 1°F increase in temperature anomaly in a county leads to 0.69 percentage points increase in loan denials for "collateral" reason, which explains 78.4% (=0.0069/-0.0088) of the effect of temperature anomaly on loan approval rate. In sharp contrast, column (2) shows that the estimated coefficient on *Temperature anomaly* is insignificant when the dependent variable is *Loan denial for other reasons*. The result provides further evidence that the lower loan approval rate following abnormally warm weather is likely due to lenders' rising concern about potential collateral damage brought by climate change.

[Insert Table 3 Here]

In addition to loan approval rate, we also examine whether unusually high temperature has any effect on the amount of mortgage loans originated. Table 4 reports the results when the dependent variable is the natural log of loan amount. In columns (1) and (2), the estimated coefficient on

[30] Loan denial reasons include loan-to-income ratio, employment history, credit history, collateral, insufficient cash, unverifiable information, credit application incomplete, mortgage insurance denied, and other unclassified reasons. Although the disclosure of denial reason is not mandatory, most loan denial reasons are reported. Please see Cortes et al. (2016) for more details.

[31] Loan officer may report as many as three reasons. We identify the loan denial due to collateral reason if at least one reason mentioned is "collateral".

[32] We first apply the same method as *Loan denial for collateral reason* to construct loan denial for loan-to-income ratio, employment history, credit history, insufficient cash, unverifiable information, credit application incomplete, mortgage insurance denied, and other unclassified reasons. The *Loan denial for other reasons* is the sum of all these reasons.

Temperature anomaly is significantly negative with a magnitude of -0.0845 and -0.0665, respectively. The estimated coefficient in column (2) implies that a 1°F increase in temperature anomaly in a county lead to 6.65% lower mortgage loans originated in a year. In dollar terms, this translates into a $1.26 ($12.69) million reduction in originated loans for a median (mean) county-year. We then break the temperature anomalies into quintiles and report the results in columns (3) and (4). The coefficient estimates on quintile dummies in column (4) are all negative, and the economic magnitude monotonically increases from quintile 2 to quintile 5. The coefficient on *Temperature anomaly_Q5* is -0.0876, implying that a county in its warmest years has 8.76% less loans originated compared to its coldest years. The effect is much smaller for mildly warm temperatures.

[Insert Table 4 Here]

Table 5 reports the regression results when the dependent variable is loan interest rate. Since the data used in this test is different from Table 3 and 4, we control for borrower FICO score, loan-to-income ratio, loan-to-value ratio, and loan term. As the geographic unit of the data is at zip code level, we control for zip code fixed effects and state*year fixed effects. In columns (1) and (2), the estimate coefficient on *Temperature anomaly* is insignificant and close to zero. Similarly, when we break the temperature anomalies into quintile ranks, we find no significant effect of temperature anomaly on loan interest rate. Overall, the insignificant result on loan interest rates suggests that lenders subjective concerns about climate change mainly manifest through adjusting approval decision instead of loan pricing. This is consistent with prior literature that loan pricing is determined mainly by computerized bank algorithms that rely on hard information, such as the borrower's FICO score, loan-to-value ratio, and documentation level, with little input from the loan officer (Rajan, Seru, and Vig, 2015).

One caveat about the insignificant effect on loan interest rate is that our data for this test only includes conforming loans, which are loans that meet the funding criteria of Freddie Mac and Fannie Mae and are eligible to be sold to these two GSEs. As a result, lenders who originate conforming loans do not need to hold them on their balance sheets, and hence have less incentives to charge higher interest rates even when they are concerned about climate change risk. The sample difference helps reconcile our results with Nguyen et al. (2020), who find lenders charge higher interest rates for mortgages on properties exposed to a greater risk of sea level rise (SLR). Their loan interest rate dataset includes both conforming and non-conforming loans, and they further show that the pricing of SLR is more pronounced when the loans are not eligible to be sold to GSEs (non-conforming loans).

[Insert Table 5 Here]

To show the monotonic effect of temperature anomalies on mortgage lending, in Figure 2 we plot the coefficients on quintile dummies of temperature anomaly, along with the 95% confidence intervals. Overall, the results suggest that mortgage lenders do take into account the impacts of climate change when originating mortgages, especially after they experience unusually warm temperatures.

[Insert Figure 2 Here]

Finally, we examine whether loans originated following periods of high abnormal temperatures have differential ex-post performance compared to those originated in other periods. We measure loan performance as the fraction of loans in a zip code-year that become 90-days delinquent within 24 months after origination. Table 6 shows that the coefficients of temperature anomaly are all close to zero and insignificant, suggesting that local temperature abnormalities have no significant effect on the ex-post loan performance, at least within the sample of conforming loans. Our finding of a non-result on loan performance differs from Deng et al. (2021), who find a significant temperature and mortgage default relationship. The loan performance data used by Deng et al. (2021) is from Moody's Analytics BlackBox (BBX), and they only keep private-labeled securitized mortgages in the analysis. Private-label mortgage loans are securitized mortgages that do not conform to the criteria set by the GSEs. The mortgages that make up these securities do not have the backing of the government and as a result carry a significantly greater risk. It is possible that within this risky set of loans and less creditworthy borrowers, prolonged high temperatures lead to higher default probability. As the effects of temperature anomalies on the interest rate and ex-post loan performance are insignificant, we focus on loan approval rate and loan amounts in our subsequent analyses.

[Insert Table 6 Here]

4.3 Local Temperature and Localized Mortgage Lending Decision

Our baseline result shows that loan officers' perceptions and concerns about climate change affect their mortgage lending decisions. This finding is built on a crucial underlying assumption that mortgage approval decisions are made locally (Cortes, Duchin, and Sosyura, 2016). In other words, loan officers and the property for which the mortgage application is made are in the same (or maybe nearby) county. In this subsection, we conduct two tests to further substantiate this assumption.

First, we re-run the baseline tests of Table 3 and 4 for small and large lenders separately. We define small (large) lenders as those belonging to the bottom (top) quartile of all lenders based on the number of states operated by lenders each year. The motivation for this subsample test is that loan officers in smaller banks are likely to have less automated approval decisions and more likely to be confined to the bank's small geographic area. As such, loan officers' concern about climate change should impact the approval decision more significantly in smaller banks as compared to large banks. Consistent with our prediction, columns (1) and (2) of Table 7 show that the coefficients of *Temperature anomaly* are -0.0185 and -0.0069 for small and large lenders, respectively. Although both are statistically significant, the economic effect of abnormal temperatures on mortgage approval rate is almost two times stronger for smaller lenders compared to larger banks. We find similar results for loan amounts, as reported in columns (3) and (4). The economic effect of abnormal temperature on loan amounts in small banks double the effect for large banks. The last row reports the *p*-values from the *F*-test for testing the differences in the coefficient on *Temperature anomaly* between the two subsamples. In both cases, the difference in the coefficient of *Temperature anomaly* between small and large banks is significant.

Our second test utilizes the granularity of the data by comparing the loan origination decision of the same lender in different counties with exposure to different temperature anomalies. Specifically, we test the effect of temperature anomaly on loan approval rate and loan amounts at the lender-county-year level and control for lender*year (and county) fixed effects. Table B2 shows the coefficients of *Temperature anomaly* are still negative and highly significant for both the approval rate and loan amounts. As we include lender*year fixed effects in this specification, the result suggests that the loan officer located in an abnormally hot county approve fewer mortgage applications and originate lower amount of loans, when compared to another loan officer in the same bank but located in a county with normal temperatures. Overall, we believe these results provide strong evidence that mortgage approval decisions are indeed made locally by loan officers, who are likely affected by idiosyncratic local shocks.

[Insert Table 7 Here]

4.4 Disentangling the Channels of Credit Demand and Supply

Temperature shocks could affect mortgage lending through both the credit demand and the supply channel. On the demand side, studies have shown that higher temperatures negatively affect labor productivity, industrial and agricultural output, and aggregate economic growth. The deteriorating local economic fundamentals could then drive firms to relocate and residents to migrate out, reduce local employment opportunities, and shrink the tax base of local governments. As a result, demand for mortgage credit could be adversely affected by abnormally high temperatures, even though lenders' willingness to supply credit has not changed.

Our empirical specifications help disentangle the two channels. First, we use state*year fixed effects to absorb (both observed and unobserved) time-varying state-level economic conditions, which may affect the demand for mortgage credit. We also include county-level employment growth, wage growth, and population growth to account for *county-level* economic fundamentals. Second, we find a significant effect of temperature anomaly on loan approval rate. Conceptually, the loan approval rate is the ratio of the number of loan applications approved to the number of loan applications reviewed in a county-year. This makes it a relatively clean measure of lenders' willingness to supply mortgage credit conditional on the demand for credit. However, one may be concerned that the quality of mortgage applicants may deteriorate in counties experiencing sustained high temperatures (possibly due to out-migration), which could then affect loan approval rate. To test this possibility, we regress the average characteristics of mortgage applicants in a county on temperature anomaly. The results in Table B3 show that counties experiencing abnormally high temperatures indeed have lower quality mortgage applicants, as measured by higher loan-to-income ratios and lower income levels, although it has no effect on the number of applicants. Since we control these characteristics of mortgage applicants in the regression, the effect of temperature anomaly on loan approval rate should not be entirely driven by its effect on the quality of loan applicants.

To further rule out the credit demand channel, we conduct several additional tests. First, we use natural disasters hitting neighboring counties as an alternative shock to beliefs about climate change (Alok et al., 2020; Correa et al., 2021). The idea is that lenders' concern about climate change could rise after observing climate change-related natural disasters in neighboring counties, but these disasters are unlikely to affect the county's economic conditions. Following Correa et al. (2021), we first classify climate change-related disasters as hurricanes, flooding, and wildfire.[33] The data is obtained from SHELDUS (Spatial Hazard Events and Losses Database for the United States). We then identify counties not affected by climate change-related disasters, but whose neighboring counties are affected by these disasters ("indirect disasters"). We examine the impact of indirect climate change-related disasters on mortgage origination by regressing *Loan approval rate* (and *Ln(Loan amount)*) on *Indirect climate disasters*. *Indirect climate disasters* is defined as, for each unaffected county, the number of neighboring counties experiencing climate change-related disasters in a year. The results in Table B4 show a significantly negative effect of *indirect climate disasters* on both loan approval rate and loan amount. Since neighboring climate-related disasters have no direct effects on the focal

[33] We focus on disasters with aggregate damages exceeding one million USD in 2016 constant dollars.

county's economic fundamentals, the evidence is most consistent with a belief updating channel in which lenders' heightened belief about climate change leads to lower mortgage origination.

Secondly, we re-run our baseline regression on a subsample of counties that have experienced strong demand growth for mortgage credit, as measured by the above average growth rate in the number of mortgage applicants and in the amount of loans applied. We continue to find a significant and negative effect of temperature anomaly on mortgage origination in this subsample, as shown in Panels A and B of Table B5.

4.5 Alternative Supply-side Explanation

As we find counties experiencing abnormally high temperatures have lower quality mortgage applicants, the lower approval rate could simply be explained by lenders' greater concern for mortgage default risk. Admittedly, it is difficult to fully rule out this explanation as changes in loan applicant quality may be unobservable to econometricians. In this subsection, we conduct two tests to evaluate this alternative supply-side explanation.

4.5.1 Temperature Anomaly and Mortgage Lending: Fintech Lenders

Our first test is a falsification test using the sample of Fintech mortgage lenders. As argued by Buchak et al. (2018) and Fuster et al. (2019), for Fintech lenders, the application and review process for mortgages is almost entirely conducted online, and no human loan officers are involved in the decision-making process. As a result, if temperature anomalies affect mortgage lending through its effect on loan officers' climate change beliefs, we should expect to find no effect for mortgage loans originated by Fintech lenders. On the other hand, if the effect we document is due to higher mortgage default risk in areas with abnormally high temperatures, we should find a similar negative effect for loans originated by Fintech lenders. Yet another possibility is that we may find a positive effect of temperature anomalies on Fintech mortgage lending. This prediction will hold if Fintech lenders (partially) fill the credit demand gap left by traditional lenders in areas with abnormally hot weather, as they can adjust supply more elastically (Fuster et al., 2019).

We follow Buchak et al. (2018) and identify seven Fintech lenders including QuickenLoans (from 2000), CashCall (from 2008), Guaranteed Rate (from 2008), Amerisave (from 2008), Homeward (from 2012), Movement (from 2013), and Summit Mortgage (from 2007). We then re-run the baseline regressions of approval rate and loan amount on temperature anomaly using this sample. Table 8 shows that the effect of temperature anomalies on mortgage lending of Fintech lenders is significantly positive and monotonically increasing. The positive effect of temperature anomaly on Fintech lending is difficult to explain by the default risk channel, under the assumption that higher default risk should affect non-Fintech and Fintech lending similarly. Instead, the result suggests that Fintech lenders fill the credit demand gap left by traditional lenders, as they are not influenced by climate change beliefs.

[Insert Table 8 Here]

4.5.2 Temperature Anomaly and Mortgage Lending: Within-County Analysis

Secondly, we conduct a more granular analysis at the lender-county-year level and add county*year fixed effects and lender*year fixed effects. The inclusion of county*year fixed effects allows us to compare different lenders' mortgage approval decisions in response to abnormally hot temperatures in the same county. Based on our previous discussions, we conjecture that mortgage lending decisions made by smaller lenders should be more sensitive to local temperature shocks, as such loan officers are likely to have more discretionary approval decision-making compared to those in larger lenders. We thus create a dummy variable, *Small lender*, that equals to one for lenders in the lowest quartile of all lenders based on the number of states operated by lenders each year. We interact the dummy with *Temperature anomaly* and run the baseline analysis at the lender-county-year level. Table 9 shows that the coefficient of interest, *Temperature anomaly*Small lender*, is significantly negative for both loan approval rate and loan amounts. Note that the county*year fixed effects absorb *Temperature anomaly* itself and all time-varying local economic conditions that may affect mortgage approval decision through the default risk channel. Under the assumption that lenders of different size lending to the same county face the same pool of mortgage applicants (and same default risk), the stronger sensitivity of smaller lenders' approval decision to temperature anomaly suggests that our result is unlikely entirely driven by deteriorating applicant quality in counties experiencing hot temperatures.

[Insert Table 9 Here]

4.6 Robustness Checks

In this section, we conduct a battery of robustness tests to address several additional concerns.

4.6.1 Controlling for House Price Index

Several recent papers (Bernstein et al., 2019; Baldauf et al., 2020) show that real estate exposed to the risk of sea-level rise sell at a significant discount relative to otherwise similar properties. Since mortgages are usually collateralized by properties, lower house prices in a region due to concerns about sea-level rise could reduce the demand for mortgage credit. To test this conjecture, we add the county-level house price index in our baseline regression and report the results in Table B5 Panel C.[34] We find the effect of temperature anomaly on mortgage origination survives when we control for house price index. This result suggests that the negative effect of abnormal temperatures on mortgage lending seems to operate independently from the house price channel.

4.6.2 Removing the House Price Bust and Subprime Mortgage Crisis Period

A second concern is that our results might be driven by the significant contraction of mortgage lending during the period of house price bust and subprime mortgage crisis, although our use of state*year fixed effects alleviates this concern. To further address this issue, we exclude the house

[34] We do not control for the house price index in our baseline regression because the house price index data cannot perfectly match to our HDMA sample. As a result, adding the house price index will reduce the sample size by 21%.

price bust and subprime mortgage crisis period (2006-2010) from our sample and re-run the baseline regressions. The results are reported in Table B5 Panel D. We continue to find a significant and negative effect of temperature anomalies on mortgage origination, suggesting that our finding is not affected by the subprime mortgage crisis.

4.6.3 Controlling for the Effect of Natural Disasters

A third concern is that local abnormal temperatures might be correlated with the frequency and magnitude of natural disasters in an area, and prior literature shows that natural disasters affect bank credit supply (Cortes and Strahan, 2017). To rule out this alternative, we control the damages caused by natural hazard at county-year level in the regression. The natural hazard damage is the per capita damage caused by natural hazards, including coastal flood, hurricane, tornado, storm, and wildfire from SHELDUS. The results are reported in Table B5 Panel E. We continue to find a significant and negative effect of temperature anomalies on mortgage origination, suggesting that our finding is not driven by the impact of natural disasters on credit supply.

4.6.4 Controlling for National Flood Insurance Program

For mortgages sold to Government-Sponsored Enterprise (GSEs), mortgage lenders in the U.S require any residence within FEMA Special Flood Hazard Areas (SFHAs) to purchase flood insurance. The SFHAs are commonly referenced as those within the 100-year flood plain boundaries. As a result, one may argue that climate risks are mostly borne by insurance companies. However, various reasons suggest that in reality mortgage lenders may still be exposed to climate risks. First, Kousky (2018) finds both the number of NFIP (National Flood Insurance Program) flood insurance policies and their total dollar amounts have declined substantially since 2006. Second, policyholders may not maintain their flood insurance over time. A study of NFIP policies between 2001 and 2009 found that the median tenure was only two to four years (Michel-Kerjan et al., 2012). Third, climate change may impose risks on real estate located in areas that are normally considered safe. With the future of flood insurance in doubt, climate change may lead to potentially significant losses for mortgage lenders. To further address this concern, we exclude from our sample five states including California, Florida, Louisiana, New Jersey, and Texas that jointly account for nearly 70% of NFIP policies (Kunreuther and Michel-Kerjan, 2011), and re-run the baseline regressions. The results are reported in Table B5 Panel F. We continue to find a significant and negative effect of temperature anomalies on mortgage origination in this sample.

4.6.5 Serial Correlation in the Temperature Anomaly Measure

We use the 36-month moving average of the temperature anomaly as the explanatory variable. This can potentially generate serial correlation issues and can affect the estimation. To address this concern, we conduct a placebo test by assigning randomly some counties to the top quintile with the highest temperature anomaly each year. We then estimate the same specifications as in column (4) of Table 3 Panel A and Table 4, respectively, using the pseudo indicator *Temperature anomaly_Q5* as the key explanatory variable. We repeat this procedure 500 times and save the coefficient estimates on the indicator *Temperature anomaly_Q5*. Graph A of Figure 3 plots the density of the coefficient estimates of *Temperature anomaly_Q5* when the dependent variable is *Loan approval rate*. The dash line represents the actual coefficient of *Temperature anomaly_Q5* from column (4) of Table 3 Panel A. Graph B of Figure 3 shows the distribution of the placebo estimates when the dependent variable is *Ln(Loan amount)*. The dash line represents the actual coefficient estimate from column (4) of Table 4. Both figures show clearly that the actual coefficient of *Temperature anomaly_Q5* falls in the extreme left tail of the distribution of placebo estimates, suggesting that the significant effect of temperature anomaly in our main analysis is unlikely caused by serial correlation issue.

5. Mechanisms

In this section, we conduct several tests to shed light on the belief updating mechanism underlying the documented effects of temperature anomalies on mortgage lending.

5.1 Sea-Level Rise Risk

The results so far suggest a strong negative effect of local temperature anomaly on mortgage origination. The mechanism we propose in this paper is that lenders' heightened belief about climate change, as induced by high local temperature, affects their loan approval decision. In other words, rising local temperatures serve as a "wake-up" call that alerts lenders to the risks of climate change. One of the most salient climate risks that matters for real estate is sea-level rise (SLR) (Hauer et al., 2016; Rao, 2017). As a result, if loan officers' concern about climate risks lead to their cautious mortgage lending decision, the effect should be particularly strong in regions most heavily exposed to sea-level rise risks.

To test this prediction, we obtain a sea-level rise risk measure from Hallegatte et al. (2013) and group all counties into regions exposed and not exposed to sea-level rise risk.[35] The list of counties exposed to sea-level rise risk is in Appendix C Table C1. We then interact a dummy variable "Sea-level rise" with the temperature anomaly and report the regression results in Table 10. Supporting our conjecture, the coefficients on *Temperature anomaly*Sea level rise* are significantly negative for both *Loan approval rate* and *Ln(Loan amount)*. The coefficient estimates suggest that a 1°F increase in the past 36-month average temperature anomaly in a county exposed to sea-level rise risk reduces the mortgage approval rate by 2.0 percentage points and the loan amount by 21.2%. This effect is about 1.5 times stronger than that on counties not exposed to the risk of sea-level rise. Our finding thus

[35] Hallegatte et al. (2013) estimate the expected mean annual loss as a percentage of a city's GDP, assuming a 40 centimeter rise in sea level while the city adapts a protection level to its optimistic bound (e.g., upgrading dikes and sea walls). The measure also takes into account a city's socio-economic conditions such as its exposed population and assets based on elevation, as well as infrastructure-based adaption.

complements several recent studies (Bernstein et al., 2019; Painter, 2020) documenting that the sea-level rise risk is priced in real estate and municipal bonds prices.

[Insert Table 10 Here]

5.2 Difference-In-Differences Analysis around the Stern Review

The "belief updating" mechanism we propose in this paper relies on a key assumption that loan officers are able to connect higher local temperatures to a larger narrative of climate change. This should be more likely when the public overall become more aware of climate risks. To provide further evidence for this mechanism, we conduct a difference-in-differences analysis using a quasi-natural experiment surrounding the release of the Stern Review in 2006, which significantly increases the public's awareness of climate change. In addition, a shocking documentary film, "*An Inconvenient Truth*", which was released around the same time (October 2006), may also help raise people's awareness of global warming.

On October 30, 2006, economist Nicholas Stern published a report detailing the costs of damage that climate change is expected to have on the global economy. The "Stern Review" is one of the earliest and most thorough analyses of the economics of climate change and one of the most well-known. After the release of the Stern Review, it is likely that lenders became more aware of the potential risk climate change may impose on their mortgage loans.[36] As shown by Painter (2020), the Stern Review significantly increased the market attention (measured by Google search volume) toward climate change. On the other hand, the Stern Review is unlikely to change the likelihood or physical risk of climate change. As a result, we expect that the effect of temperature anomalies on mortgage origination will be greater after the release of the Stern Review.

In Table 11, we conduct a difference-in-differences analysis to examine whether increased awareness of climate risks leads to a greater effect of abnormal temperatures on mortgage lending. We

[36] For example, Kass and McCarroll (2006) cite the Stern Review when making the following prediction about financial institutions: "Insurance companies, investors and lending institutions will, after the initial losses, begin to introduce (as some insurers already are) screening standards designed to identify climate change risks."

create a dummy variable *Stern Review*, which is equal to one if the year is within the 3-year period after the Stern Review was released (i.e., 2007, 2008 and 2009), and equal to zero if the year is within the 3-year period before the Stern Review was released (i.e., 2003, 2004 and 2005). The results reveal that prior to the release of the Stern Review, *Temperature anomaly* has no significant effect on *Loan approval rate* and *Loan amount*. In contrast, lenders began to account for climate risks after the release of the Stern Review, as the coefficients on *Temperature anomaly*Stern review* are negative and significant for both *Loan approval rate* and *Loan amount*. The coefficient estimates on *Temperature anomaly*Stern review* suggest that after the release of the Stern Review, a 1°F increase in the past 36-month average temperature anomaly in a county reduces the mortgage approval rate by 2.1 percentage points and the loan amount by 9.7%. These effects are considerably larger than what is observed in the full sample.

[Insert Table 11 Here]

To provide further evidence on the crucial role of public awareness of climate change, we examine whether temperature shocks exert a stronger effect on mortgage origination in times of heightened media coverage on climate change topics. The idea is that public awareness of climate change is likely higher when there is intensive media coverage on this topic. To that end, we use the newspaper coverage on climate change or global warming from Boykoff et al. (2019) as a proxy for media attention.[37] We aggregate the monthly measure to annual level and interact the *Newspaper coverage* measure with the *Temperature anomaly* and expect the interaction term to be significantly negative in the regression. Table 12 presents the regression results. We find that the coefficients of the interaction term *Temperature anomaly*Newspaper coverage* are indeed negative, and significantly so for loan approval rate.

[37] The data measures the monthly newspaper coverage on climate change or global warming based on five widely circulated national newspapers including *Washington Post, Wall Street Journal, New York Times, USA Today, and Los Angeles Times*.

In sum, both the difference-in-differences analysis around the Stern Review and time-series variation of media coverage on climate change suggest that lenders more likely associate abnormally high local temperature with the larger narrative of global warming after they become more aware of climate change and take actions accordingly.

[Insert Table 12 Here]

6. Conclusion

In this paper, we examine whether agents' perceptions and concerns about climate change affect their real decision-making. Using mortgage origination as a laboratory, we find a strong negative effect of abnormally high local temperatures on mortgage lending at the U.S county level. The economic effect is non-trivial. A 1°F increase in the past 36-month average temperature anomaly in a county reduces the mortgage approval rate by about 0.88 percentage points and the loan amount by 6.65% on average. This effect is stronger among counties heavily exposed to the risk of sea-level rise, during periods of heightened public attention to climate change, and for loans originated by small lenders. Additional tests suggest that the negative relation between temperature and approval rate is not fully explained by changes in local economic conditions and demand for mortgage credit, or deteriorating quality of loan applicants.

The evidence found in this paper has important real-world implications. The size and importance of mortgages (and its derivative securities) on household balance sheets should make the impacts of climate risks a first-order concern for millions of households and financial institutions. On the policy side, policymakers have been increasingly concerned about the systematic risks posed by climate change on financial stability. Our study reveals that lending institutions are aware of the risks that climate change poses to the quality of their mortgage loans and are taking these risks into account when originating mortgages.

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Figure 1. Beliefs about Climate Change

Figure 1a shows the fraction of adults at U.S. counties who are somewhat/very worried about global warming in 2014. Figure 1b shows the fraction of adults at U.S. counties who think global warming is already harming people in the United States now/within 10 years. The data is from Yale Climate Opinion Maps.

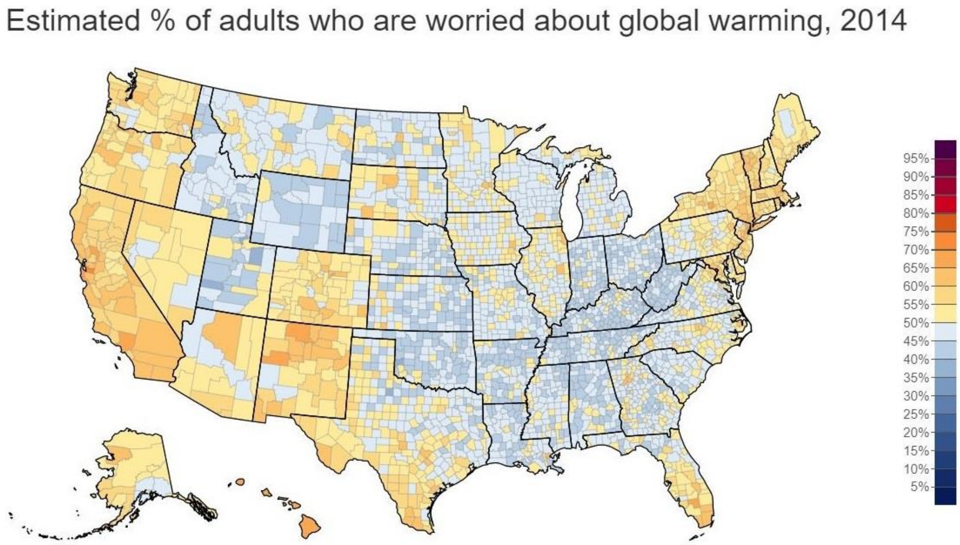


Figure 1a

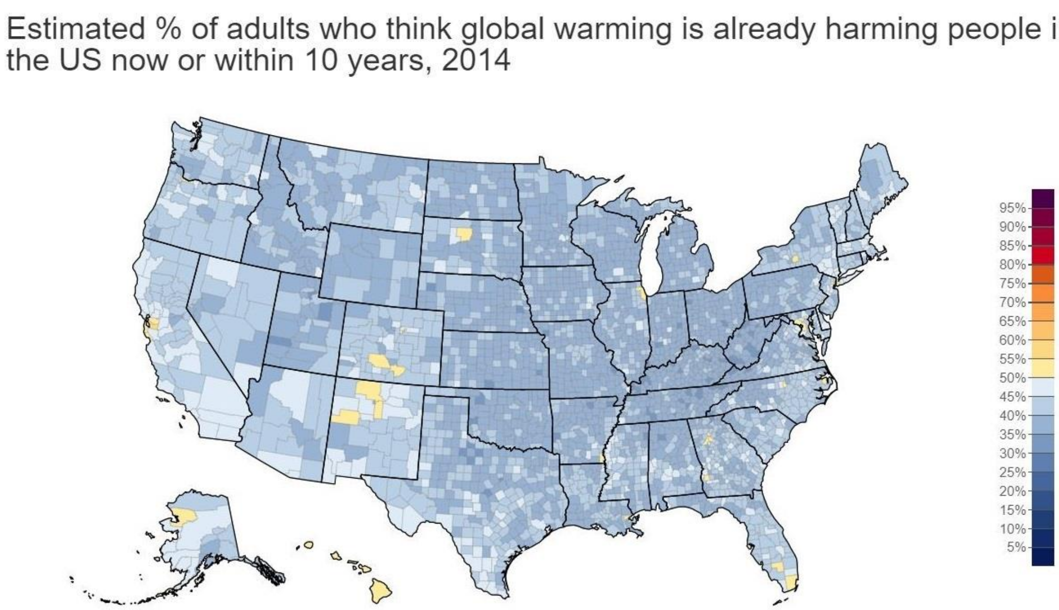
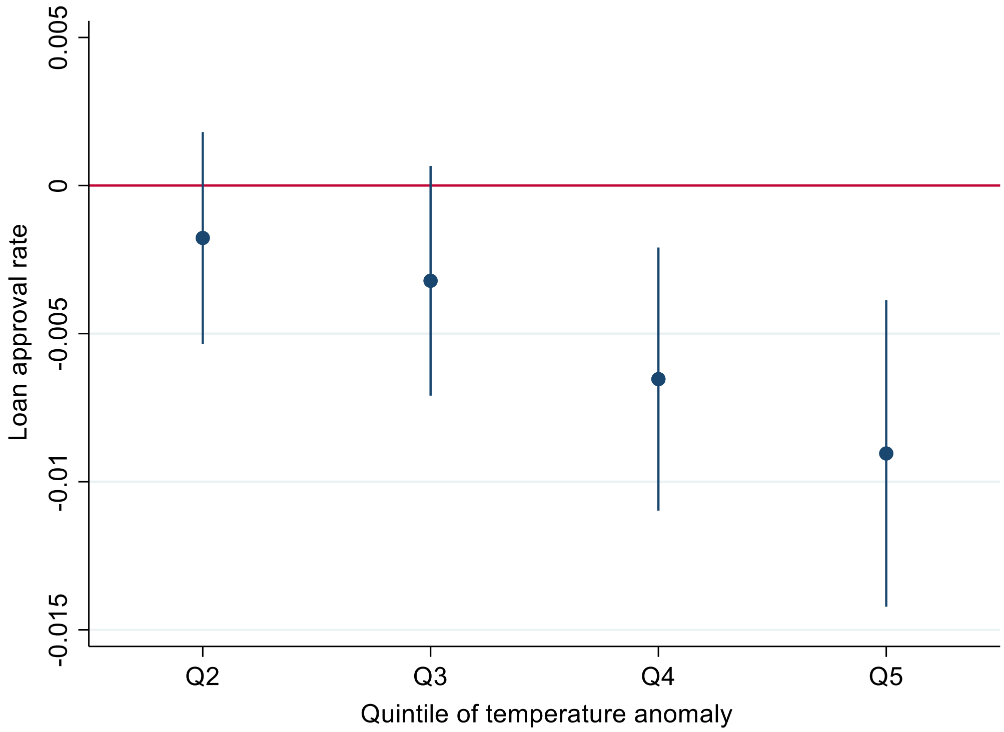
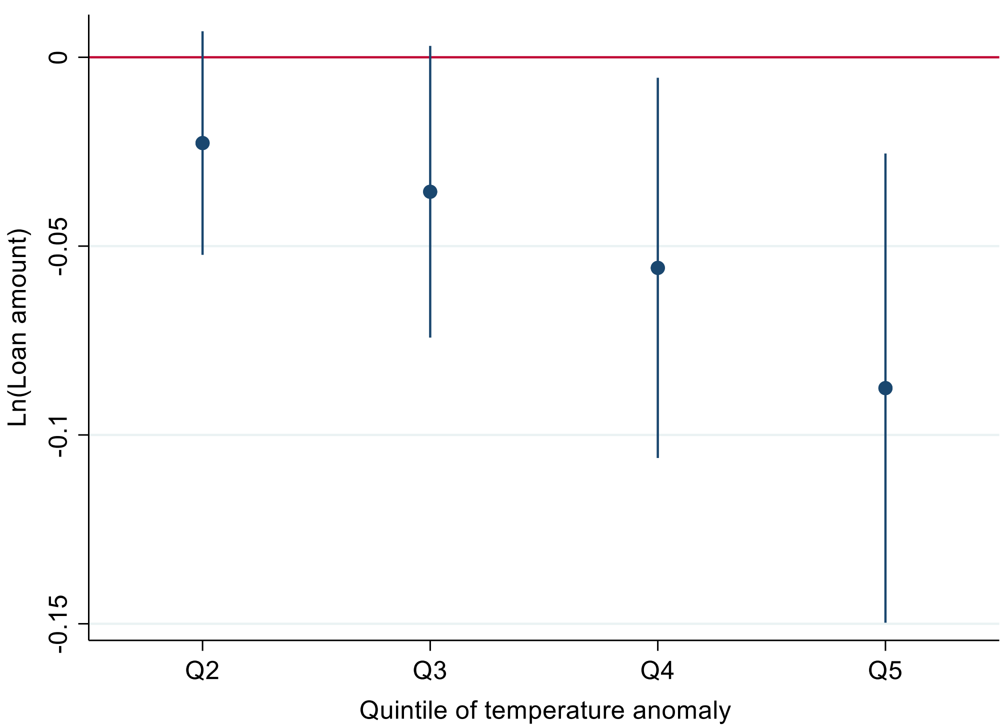


Figure 1b

Figure 2. Temperature Anomaly and Loan Approval Rate & Loan Amount: 1990-2016

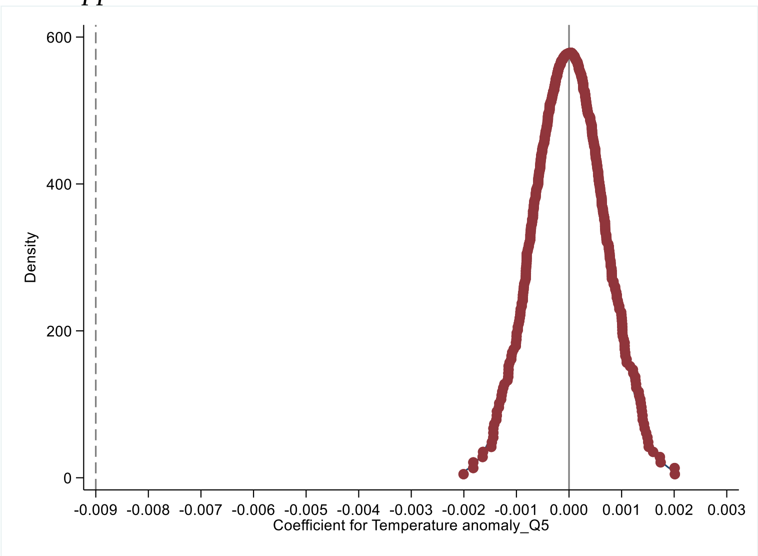




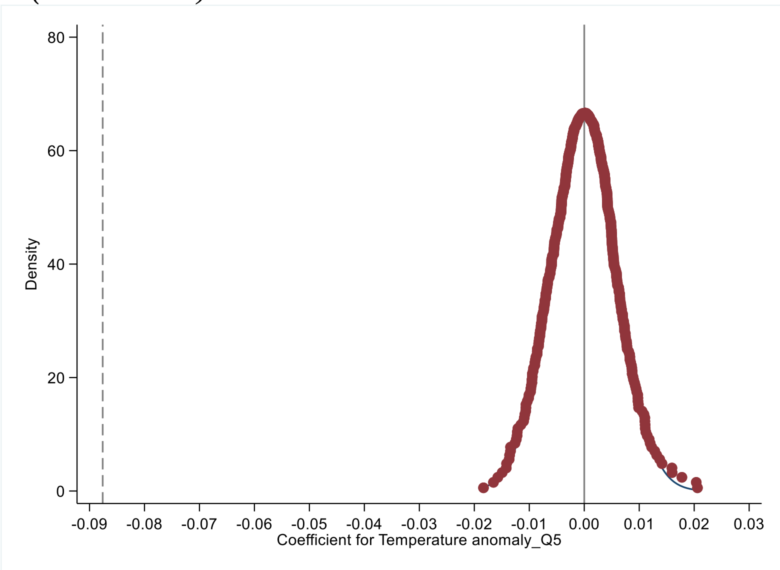
The figure plots the coefficient estimates from the regressions (1a) and (1b). The dependent variables are the *loan approval rate* and *Ln(loan amount)*. The independent variables are quintile dummies that equal to one if a county belongs to quintile 2 to quintile 5 of temperature anomalies. We control for borrower characteristics, county-level macroeconomic variables, and county and state*year fixed effects in the regression. Variable definitions are in Appendix A. The sample period is from 1990 to 2016.

Figure 3. Placebo Test

Graph A: Density of the estimated coefficient of *Temperature anomaly_Q5* when dependent variable is *Loan approval rate*



Graph B: Density of the estimated coefficient of Temperature anomaly_Q5 when dependent variable is *Ln(Loan amount)*



This figure plots the density of the estimated coefficient on the placebo *Temperature anomaly_Q5* from 500 bootstrap simulations of the specification (4) in Table 3 and Table 4, respectively. Specifically, we randomly assign a county to be in the top quintile of temperature anomaly each year. We then estimate the same specification as in column (4) of Table 3 and Table 4, and save the coefficient estimates on the indicator variable *Temperature anomaly_Q5*. We repeat this procedure 500 times. Graph A plots the density of the coefficient estimates when the dependent variable is *Loan approval rate*. The dash line represents the actual coefficient from column (4) of Table 3 Panel A. Graph B shows the density of the coefficient estimates when the dependent variable is *Ln(Loan amount)*. The dash line represents the actual coefficient from column (4) of Table 4.

Table 1 Summary Statistics

This table reports summary statistics of all the variables used in the paper. Panel A reports the summary statistics for the HMDA sample. We first calculate the statistics of all variables at the county level and then report the mean of these county-level summary statistics. Panel B reports summary statistics for the Fannie Mae and Freddie Mac (F&F) sample. We first calculate the statistics of all variables at the-3-digit zip code-level and then report the mean of these zip code-level summary statistics (*Abnormal_SVI* is at DMA-level).

Panel A: Summary Statistics for the HMDA Sample

	Mean	Standard Deviation	25th percentile	Median	75th percentile
Climate change measures					
Temperature anomaly	1.0746	0.2482	0.8931	1.0736	1.2503
Borrower and loan characteristics					
Loan approval rate	0.7046	0.0824	0.6400	0.7046	0.7564
Loan denial for collateral reason	0.2052	0.0460	0.1759	0.2045	0.2318
Loan amount (in million)	190.7746	100.9206	5.2841	18.8995	74.5747
Ln(Loan amount)	9.5558	2.1434	8.0421	9.3355	10.9509
Loan-to-income	1.6709	0.3376	1.4270	1.6181	1.8707
Income (in thousand)	63.2623	16.9842	52.4876	58.8058	68.3129
Ln (Income)	4.0741	0.2323	3.9180	4.0285	4.1800
Fraction of minority applicants	0.2241	0.1148	0.1467	0.1826	0.2698
Ln (# of applicants)	6.4518	1.8371	5.2020	6.3132	7.6062
Macroeconomics characteristics					
Employment growth	0.0095	0.0113	0.0024	0.0083	0.0153
Wages growth	0.0402	0.0137	0.0316	0.0391	0.0471
Population growth	0.0055	0.0101	-0.0012	0.0041	0.0103
Other variables					
Worry	0.4876	0.0505	0.4500	0.4800	0.5200
Timing	0.3966	0.0350	0.3700	0.3900	0.4200
Sea-level rise	0.0122	0.1100	0.0000	0.0000	0.0000

Panel B: Summary Statistics for the Fannie Mae and Freddie Mac (F&F) Sample

	Mean	Standard Deviation	25th percentile	Median	75th percentile
Borrower and loan characteristics					
Loan interest rate	0.0533	0.0007	0.0529	0.0532	0.0537
Default rate	0.0105	0.0118	0.0028	0.0062	0.0137
FICO	739.2942	6.5408	735.8649	740.0411	743.8134
Loan-to-value	0.7313	0.0332	0.7181	0.7393	0.7531
Loan-to-income	0.3283	0.0250	0.3101	0.3255	0.3450
Loan term	308.3290	11.8941	300.9055	308.0617	316.3272
Other variables					
Abnormal_SVI	-0.2290	1.1578	-0.5486	0.000	0.3514

Table 2 Temperature Anomaly and Public Attention to and Belief about Climate Change

This table presents the regression results of temperature anomaly on the public attention to and belief in climate change. The independent variables in both panels are *Temperature anomaly* and *Temperature anomaly_Q2-Q5*. *Temperature anomaly* is the county-level 36-month average temperature anomaly. A positive (negative) *temperature anomaly* represents a temperature warmer (cooler) than the 30-year (from 1961- 1990) average temperature in the county. *Temperature anomaly_Q2-Q5* are quintile dummies that equal to one if a county is in the corresponding quintile of *Temperature anomaly*. Panel A presents the impact of temperature anomaly on attention to global warming. The dependent variable *Abnormal_SVI* is the natural log of one plus the (seasonally adjusted) monthly Google search volume index (SVI) of the topic "Global warming". The unit of analysis is at DMA (Designated Market Area)-month level, and the sample period is from April 2004 to December 2016. Standard errors in parentheses are two-way clustered at DMA and Year-Month level. Panel B presents the impact of temperature anomaly on climate change beliefs. The dependent variables are *Worry* and *Timing*, which measure the fraction of adult population in a county who are somewhat/very worried about global warming and who think global warming will start to harm people in the United States now/within 10 years, respectively. The unit of analysis is county-year level, and the sample period is from 2014 to 2018. Standard errors in parentheses are clustered at year level. Variable definitions are provided in Appendix A. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Temperature Anomaly and Attention to Global Warming

Variable	Abnormal_SVI	
	(1)	(2)
Temperature anomaly	0.0234**	
	(0.0113)	
Temperature anomaly_Q5		0.0477**
		(0.0229)
Temperature anomaly_Q4		0.0038
		(0.0230)
Temperature anomaly_Q3		0.0078
		(0.0265)
Temperature anomaly_Q2		0.0019
		(0.0229)
Constant	-0.2605***	-0.2411***
	(0.0179)	(0.0182)
Year*Month fixed effects	YES	YES
Adj. R^2	0.1545	0.1545
N	30,447	30,447

Panel B: Temperature Anomaly and Climate Change Beliefs

Variable	Worry		Timing	
	(1)	(2)	(3)	(4)
Temperature anomaly	1.1748***		0.7916***	
	(0.0532)		(0.0691)	
Temperature anomaly_Q5		2.0558**		1.4317**
		(0.3522)		(0.3044)
Temperature anomaly_Q4		0.7637***		0.4793**
		(0.1081)		(0.0989)
Temperature anomaly_Q3		0.0542		-0.0407
		(0.1019)		(0.0997)
Temperature anomaly_Q2		0.0846		0.0220
		(0.1542)		(0.1344)
Constant	49.2899***	50.2778***	41.6158***	42.3016***
	(0.0716)	(0.0986)	(0.0930)	(0.0947)
State*Year fixed effects	YES	YES	YES	YES
Adj. R^2	0.4869	0.4891	0.5411	0.5429
N	12,421	12,421	12,421	12,421

Table 3 Temperature Anomaly, Loan Approval Rate, and Loan Denial Reasons

This table presents the regression results of temperature anomaly on loan approval rate and loan denial reasons. The dependent variables is *Loan approval rate* in Panel A and *Loan denial for collateral reason* and *Loan denial for other reasons* in Panel B. *Loan approval rate* is defined as the ratio of the number of loan applications approved to the number of loan applications reviewed in a county-year. *Loan denials for collateral reason* is defined as the loan denials for collateral reason as a fraction of all loan denials in a county-year. *Loan denials for other reasons* is defined as the loan denials for other reasons (not related to collateral) as a fraction of all loan denials in a county-year. The independent variables are *Temperature anomaly*, *Temperature anomaly_Quintile*, and *Temperature anomaly_Q2-Q5*. *Temperature anomaly* is the county-level 36-month average temperature anomaly. A positive (negative) temperature anomaly represents a temperature warmer (cooler) than the 30-year (from 1961- 1990) average. *Temperature anomaly_Quintile* is a rank variable, ranging from 1 to 5, for each quintile of *Temperature anomaly*. *Temperature anomaly_Q2-Q5* are quintile dummies that equal to one if a county belongs to the corresponding quintile of temperature anomaly. The unit of analysis is at county-year level, and the sample period is from 1990 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at county and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Loan approval rate

Variable	Loan approval rate			
	(1)	(2)	(3)	(4)
Temperature anomaly	-0.0117***	-0.0088***		
	(0.0023)	(0.0020)		
Temperature anomaly_Quintile			-0.0023***	
			(0.0006)	
Temperature anomaly_Q5				-0.0090***
				(0.0025)
Temperature anomaly_Q4				-0.0065***
				(0.0022)
Temperature anomaly_Q3				-0.0032
				(0.0019)
Temperature anomaly_Q2				-0.0018
				(0.0017)
Loan-to-income		-0.0034	-0.0034	-0.0034
		(0.0089)	(0.0089)	(0.0089)
Income		0.0009***	0.0009***	0.0009***
		(0.0001)	(0.0001)	(0.0001)
Fraction of minority applicants		-0.2365***	-0.2366***	-0.2367***
		(0.0203)	(0.0202)	(0.0202)
Employment growth		-0.0564***	-0.0567***	-0.0567***
		(0.0150)	(0.0150)	(0.0150)
Wages growth		0.0521***	0.0523***	0.0523***
		(0.0084)	(0.0084)	(0.0084)
Population growth		0.0723**	0.0735**	0.0733**
		(0.0349)	(0.0350)	(0.0350)
Constant	0.7088***	0.7042***	0.7017***	0.6989***
	(0.0024)	(0.0198)	(0.0197)	(0.0201)
County fixed effects	YES	YES	YES	YES
State*Year fixed effects	YES	YES	YES	YES
Adj. R^2	0.5627	0.5871	0.5870	0.5870
N	83,408	83,408	83,408	83,408

Panel B: Loan denial reasons

Variable	Loan denial for collateral reason (1)	Loan denial for other reasons (2)
Temperature anomaly	0.0069**	-0.0052
	(0.0032)	(0.0042)
Loan-to-income	-0.0046	-0.0078
	(0.0027)	(0.0051)
Income	0.0005***	-0.0007***
	(0.0001)	(0.0001)
Fraction of minority applicants	0.0221	-0.0676**
	(0.0227)	(0.0289)
Employment growth	0.0268	-0.0164
	(0.0273)	(0.0428)
Wages growth	-0.0324*	0.0233
	(0.0188)	(0.0224)
Population growth	-0.1545***	0.2405***
	(0.0527)	(0.0770)
Constant	0.1718***	1.1016***
	(0.0097)	(0.0183)
County fixed effects	YES	YES
State*Year fixed effects	YES	YES
Adj. R^2	0.3294	0.3244
N	80,635	80,635

Table 4 Temperature Anomaly and Loan Amount

This table presents the regression results of temperature anomaly on loan amount. The dependent variable is *Ln(Loan amount)*, defined as the natural log of the amount of originated loans that are not sold to other institutions at end of the year for a given county-year. The independent variables include *Temperature anomaly*, *Temperature anomaly_Quintile*, and *Temperature anomaly_Q2-Q5*. *Temperature anomaly* is the county-level 36-month average temperature anomaly. A positive (negative) temperature anomaly represents a temperature warmer (cooler) than the 30-year (from 1961-1990) average. *Temperature anomaly_Quintile* is a rank variable, ranging from 1 to 5, for each quintile of *Temperature anomaly*. *Temperature anomaly_Q2-Q5* are quintile dummies that equal to one if a county belongs to the corresponding quintile of temperature anomaly. The unit of analysis is at county-year level, and the sample period is from 1990 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at county and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Ln(Loan amount)			
	(1)	(2)	(3)	(4)
Temperature anomaly	-0.0845***	-0.0665**		
	(0.0293)	(0.0297)		
Temperature anomaly_Quintile			-0.0205***	
			(0.0074)	
Temperature anomaly_Q5				-0.0876***
				(0.0302)
Temperature anomaly_Q4				-0.0558**
				(0.0245)
Temperature anomaly_Q3				-0.0356*
				(0.0188)
Temperature anomaly_Q2				-0.0227
				(0.0144)
Loan-to-income		0.2165*	0.2164*	0.2165*
		(0.1226)	(0.1225)	(0.1226)
Income		0.0113***	0.0113***	0.0113***
		(0.0022)	(0.0022)	(0.0022)
Fraction of minority applicants		-1.9271***	-1.9277***	-1.9275***
		(0.2374)	(0.2372)	(0.2373)
Employment growth		-0.3997*	-0.4033*	-0.4020*
		(0.2307)	(0.2319)	(0.2317)
Wages growth		0.2674*	0.2694*	0.2685*
		(0.1416)	(0.1421)	(0.1422)
Population growth		1.0543***	1.0613***	1.0590***
		(0.3645)	(0.3664)	(0.3651)
Constant	9.7130***	9.0309***	9.0207***	8.9992***
	(0.0316)	(0.2215)	(0.2189)	(0.2195)
County fixed effects	YES	YES	YES	YES
State*Year fixed effects	YES	YES	YES	YES
Adj. R^2	0.9144	0.9194	0.9194	0.9194
N	81,865	81,865	81,865	81,865

Table 5 Temperature Anomaly and Loan Interest Rate

This table presents the regression results of temperature anomaly on loan interest rate. The dependent variable is *Loan interest rate*, defined as the average interest rate of loans at origination for a given zip code-year. The independent variables include *Temperature anomaly*, *Temperature anomaly_Quintile*, and *Temperature anomaly_Q2-Q5*. *Temperature anomaly* is the zip code-level 36-month average temperature anomaly. A positive (negative) temperature anomaly represents a temperature warmer (cooler) than the 30-year (from 1961-1990) average. *Temperature anomaly_Quintile* is a rank variable, ranging from 1 to 5, for each quintile of *Temperature anomaly*. *Temperature anomaly_Q2-Q5* are quintile dummies that equal to one if a zip-code belongs to the corresponding quintile of temperature anomaly. The unit of analysis is at (first 3-digit) zip code-year level. The sample period is from 2000 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at zip code and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Loan interest rate			
	(1)	(2)	(3)	(4)
Temperature anomaly	0.0001	0.0001		
	(0.0001)	(0.0001)		
Temperature anomaly_Quintile			0.0000	
			(0.0000)	
Temperature anomaly_Q5				0.0000
				(0.0001)
Temperature anomaly_Q4				-0.0000
				(0.0000)
Temperature anomaly_Q3				-0.0000
				(0.0000)
Temperature anomaly_Q2				-0.0000
				(0.0000)
FICO		-0.0000**	-0.0000*	-0.0000*
		(0.0000)	(0.0000)	(0.0000)
Loan-to-value		0.0107***	0.0107***	0.0107***
		(0.0015)	(0.0015)	(0.0015)
Loan-to-income		0.0015	0.0015	0.0015
		(0.0018)	(0.0017)	(0.0018)
Loan term		0.0000***	0.0000***	0.0000***
		(0.0000)	(0.0000)	(0.0000)
Constant	0.0531***	0.0477***	0.0477***	0.0477***
	(0.0001)	(0.0060)	(0.0060)	(0.0060)
Zip code fixed effects	YES	YES	YES	YES
State*Year fixed effects	YES	YES	YES	YES
Adj. R^2	0.9985	0.9990	0.9990	0.9990
N	12,025	12,025	12,025	12,025

Table 6 Temperature Anomaly and Loan Performance

This table presents the regression results of temperature anomaly on loan performance. The dependent variable is *Default rate*, defined as the fraction of loans that become 90-days delinquent within 24 months since origination for loans approved in a given zip code-year. The independent variables are *Temperature anomaly*, *Temperature anomaly_Quintile*, and *Temperature anomaly_Q2-Q5*. *Temperature anomaly* is the zip code-level 36-month average temperature anomaly. A positive (negative) temperature anomaly represents a temperature warmer (cooler) than the 30-year (from 1961-1990) average. *Temperature anomaly_Quintile* is a rank variable, ranging from 1 to 5, for each quintile of *Temperature anomaly*. *Temperature anomaly_Q2-Q5* are quintile dummies that equal to one if a zip-code belongs to the corresponding quintile of temperature anomaly. The unit of analysis is at (first 3-digit) zip code-year level. The sample period is from 2000 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at zip code and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Default rate			
	(1)	(2)	(3)	(4)
Temperature anomaly	-0.0001	0.0003		
	(0.0007)	(0.0006)		
Temperature anomaly_Quintile			0.0000	
			(0.0002)	
Temperature anomaly_Q5				-0.0000
				(0.0006)
Temperature anomaly_Q4				0.0002
				(0.0006)
Temperature anomaly_Q3				0.0003
				(0.0004)
Temperature anomaly_Q2				-0.0001
				(0.0003)
FICO		-0.0004***	-0.0004***	-0.0004***
		(0.0001)	(0.0001)	(0.0001)
Loan-to-value		-0.0137	-0.0136	-0.0136
		(0.0146)	(0.0147)	(0.0147)
Loan-to-income		0.0265	0.0265	0.0265
		(0.0278)	(0.0278)	(0.0277)
Loan term		0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)
Constant	0.0106***	0.2723***	0.2723***	0.2727***
	(0.0010)	(0.0596)	(0.0596)	(0.0592)
Zip code fixed effects	YES	YES	YES	YES
State*Year fixed effects	YES	YES	YES	YES
Adj. R^2	0.7485	0.7617	0.7617	0.7617
N	12,025	12,025	12,025	12,025

Table 7 Temperature Anomaly and Mortgage Lending: Subsample Analysis for Small and Large Lenders

This table presents the regression results of temperature anomaly on loan approval rate and loan amount separately for small lenders and large lenders. The dependent variables are *Loan approval rate* and *Ln(Loan amount)*. *Loan approval rate* is the ratio of the number of loan applications approved to the number of loan applications reviewed, and *Ln(Loan amount)* is the natural log of the amount of originated loans that are not sold to other institutions at the end of the year in a county. The independent variable *Temperature anomaly* is the county-level 36-month average temperature anomaly. A positive (negative) temperature anomaly represents a temperature warmer (cooler) than the 30-year (from 1961-1990) historical average. Small (Large) lenders are defined as lenders belonging to the bottom (top) quartile of all lenders based on the number of states operated by lenders each year. The last row presents p-values from the F-test for testing the differences in the coefficient on *Temperature anomaly* between the two subsamples. The unit of analysis is at county-year level. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at county and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Loan approval rate		Ln(Loan amount)	
	Small lenders	Large lenders	Small lenders	Large lenders
	(1)	(2)	(3)	(4)
Temperature anomaly	-0.0185***	-0.0069***	-0.1041*	-0.0509*
	(0.0063)	(0.0025)	(0.0524)	(0.0259)
Debt-to-income	0.1717***	0.0156	0.3417***	0.2947**
	(0.0083)	(0.0123)	(0.0213)	(0.1217)
Income	0.0046***	0.0012***	0.0046***	0.0131***
	(0.0002)	(0.0002)	(0.0004)	(0.0019)
Fraction of minority applicants	0.0488***	-0.1630***	-0.7177***	-1.6352***
	(0.0158)	(0.0358)	(0.0803)	(0.2361)
Employment growth	-0.0932*	-0.0583***	-0.8577**	-0.2736
	(0.0489)	(0.0153)	(0.3812)	(0.2038)
Wages growth	0.0896***	0.0479***	0.6898***	0.1302
	(0.0301)	(0.0093)	(0.2368)	(0.1345)
Population growth	0.1792**	0.0919**	-0.7034	0.7102**
	(0.0712)	(0.0354)	(1.2660)	(0.2626)
Constant	0.2163***	0.6103***	6.9665***	8.2348***
	(0.0214)	(0.0324)	(0.0798)	(0.2107)
County fixed effects	YES	YES	YES	YES
State*Year fixed effects	YES	YES	YES	YES
Adj. R^2	0.6816	0.5518	0.7654	0.9265
N	83,408	83,408	59,772	80,963
F-test	0.0139		0.0995	

Table 8 Falsification Tests Using Fintech Mortgage Lenders

This table presents the results using the sample of Fintech lenders. We follow Buchak et al. (2018) and identify seven Fintech lenders including QuickenLoans (from 2000), CashCall (from 2008), Guaranteed Rate (from 2008), Amerisave (from 2008), Homeward (from 2012), Movement (from 2013), and Summit Mortgage (from 2007). The dependent variables are *Loan approval rate* and *Ln(Loan amount)*. *Loan approval rate* is the ratio of the number of loan applications approved to the number of loan applications reviewed, and *Ln(Loan amount)* is the natural log of the amount of originated loans that are not sold to other institutions at the end of the year in a county. The independent variables are *Temperature anomaly*, *Temperature anomaly_Quintile*, and *Temperature anomaly_Q2-Q5*. *Temperature anomaly* is the county-level 36-month average temperature anomaly. A positive (negative) temperature anomaly represents a temperature warmer (cooler) than the 30-year (from 1961-1990) average. *Temperature anomaly_Quintile* is a rank variable, ranging from 1 to 5, for each quintile of *Temperature anomaly*. *Temperature anomaly_Q2-Q5* are dummies that equal to one if a county belongs to the corresponding quintile of temperature anomaly. The unit of analysis is at county-year level, and the sample period is from 2000 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at county and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Loan approval rate			Ln(Loan amount)		
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature anomaly	0.0075***			0.0882**		
	(0.0055)			(0.0371)		
Temperature anomaly_Quintile		0.0038**			0.0212*	
		(0.0016)			(0.0120)	
Temperature anomaly_Q5			0.0144**			0.1104**
			(0.0061)			(0.0473)
Temperature anomaly_Q4			0.0114*			0.0539
			(0.0059)			(0.0432)
Temperature anomaly_Q3			0.0076*			0.0442
			(0.0041)			(0.0323)
Temperature anomaly_Q2			0.0031			0.0437*
			(0.0040)			(0.0226)
Loan-to-income	-0.0326***	-0.0327***	-0.0327***	0.1481***	0.1481***	0.1486***
	(0.0045)	(0.0045)	(0.0045)	(0.0343)	(0.0343)	(0.0343)
Fraction of minority applicants	-0.0265**	-0.0266**	-0.0266**	-0.1286	-0.1277	-0.1282
	(0.0100)	(0.0099)	(0.0100)	(0.1000)	(0.1004)	(0.1003)
Income	0.0002*	0.0002*	0.0002*	0.0069***	0.0069***	0.0070***
	(0.0001)	(0.0001)	(0.0001)	(0.0010)	(0.0010)	(0.0010)
Employment growth	0.0014	0.0014	0.0014	0.0059	0.0060	0.0059
	(0.0009)	(0.0010)	(0.0010)	(0.0038)	(0.0038)	(0.0038)
Wages growth	-0.0002	-0.0002	-0.0002	0.0001	0.0001	0.0002
	(0.0005)	(0.0005)	(0.0005)	(0.0025)	(0.0025)	(0.0025)
Population growth	0.0441	0.0436	0.0436	0.5104	0.5037	0.5127
	(0.1113)	(0.1120)	(0.1120)	(0.5993)	(0.5960)	(0.5977)
Constant	0.7900***	0.7891***	0.7931***	5.2835***	5.3373***	5.3481***
	(0.0160)	(0.0144)	(0.0141)	(0.1711)	(0.1626)	(0.1555)
County fixed effects	YES	YES	YES	YES	YES	YES
State*Year fixed effects	YES	YES	YES	YES	YES	YES
Adj. R^2	0.2073	0.2074	0.2073	0.7978	0.7977	0.7978
N	43,972	43,972	43,972	24,122	24,122	24,122

Table 9 Temperature Anomaly and Mortgage Lending: Within-County Analysis

This table presents the regression results of temperature anomaly on loan approval rate and loan amount. The dependent variables are *Loan approval rate* and *Ln(Loan amount)*. *Loan approval rate* is the ratio of the number of loan applications approved to the number of loan applications reviewed, and *Ln(Loan amount)* is the natural log of the amount of originated loans that are not sold to other institutions at the end of the year in a county. The independent variable *Temperature anomaly* is the county-level 36-month average temperature anomaly. A positive (negative) temperature anomaly represents a temperature warmer (cooler) than the 30-year (from 1961-1990) average. *Small lender* is a dummy variable equal to one (zero) if a lender belongs to the bottom (top) quartile of all lenders based on the number of states operated by lenders each year. The unit of analysis is at lender-county-year level. Variable definitions are provided in Appendix A. Standard errors in parentheses are clustered at county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Loan approval rate (1)	Ln(Loan amount) (2)
Temperature anomaly*Small lender	-0.0057***	-0.0733***
	(0.0021)	(0.0200)
Debt-to-income	-0.0210***	0.4524***
	(0.0002)	(0.0015)
Income	0.0002***	0.0034***
	(0.0000)	(0.0000)
Fraction of minority applicants	-0.0929***	-0.2171***
	(0.0005)	(0.0039)
Constant	0.7574***	4.9600***
	(0.0005)	(0.0048)
County*Year fixed effects	YES	YES
Lender*Year fixed effects	YES	YES
Adj. R^2	0.4123	0.4481
N	8,359,613	3,416,705

Table 10 Interaction with County Exposure to Sea-level Rise

This table presents the regression results of temperature anomaly on loan approval rate and loan amount, along with its interaction with indicator of sea-level rise risk. The dependent variables are *Loan approval rate* in column 1 and *Ln(Loan amount)* in column 2. *Loan approval rate* is the ratio of the number of loan applications approved to the number of loan applications reviewed, and *Ln(Loan amount)* is the natural log of the amount of originated loans that are not sold to other institutions at the end of the year in a given county. The independent variable is *Temperature anomaly*, and its interaction with *Sea-level rise*. *Temperature anomaly* is the county-level 36-month average temperature anomaly. *Sea level rise* is dummy variable equals one if a county is exposed to sea-level rise risk according to Hallegatte et al. (2013), and zero otherwise. The unit of analysis is at county-year level, and the sample period is from 1990 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at county and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Loan approval rate (1)	Ln(Loan amount) (2)
Temperature anomaly	-0.0087***	-0.0657**
	(0.0020)	(0.0296)
Temperature anomaly * Sea-level rise	-0.0113**	-0.1462*
	(0.0046)	(0.0737)
Loan-to-income	-0.0033	0.2177*
	(0.0089)	(0.1226)
Income	0.0009***	0.0113***
	(0.0001)	(0.0022)
Fraction of minority applicants	-0.2365***	-1.9267***
	(0.0203)	(0.2369)
Employment growth	-0.0562***	-0.3965*
	(0.0150)	(0.2299)
Wages growth	0.0520***	0.2658*
	(0.0084)	(0.1409)
Population growth	0.0735**	1.0708***
	(0.0350)	(0.3622)
Constant	0.7040***	9.0285***
	(0.0198)	(0.2213)
County fixed effects	YES	YES
State*Year fixed effects	YES	YES
Adj. R^2	0.5871	0.9194
N	83,408	81,865

Table 11 Difference-in-Differences Analysis around the Stern Review

This table presents difference-in-difference estimates for the loan approval rate and loan amount in the 3-year before and 3-year after the Stern Review was released on October 30, 2006. The unit of analysis is county-year, and the sample period is from 2003 to 2009 (excluding 2006). *Stern review* is a dummy variable equals one if the year is within 3 years after the Stern Review was released and equals zero if the year is within 3 years before the Stern Review was released. *Loan approval rate* is the ratio of the number of loan applications approved to the number of loan applications reviewed, and *Ln(Loan amount)* is the natural log of the amount of originated loans that are not sold to other institutions at the end of the year in a given county. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at county and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Loan approval rate (1)	Ln(Loan amount) (2)
Temperature anomaly	0.0076	0.0396
	(0.0071)	(0.0346)
Temperature anomaly * Stern review	-0.0287***	-0.1365**
	(0.0055)	(0.0480)
Loan-to-income	-0.0404***	0.0997*
	(0.0068)	(0.0438)
Income	0.0005***	0.0089***
	(0.0001)	(0.0008)
Fraction of minority applicants	-0.1464***	-0.4840
	(0.0334)	(0.2663)
Employment growth	0.0229	0.0134
	(0.0315)	(0.1245)
Wages growth	0.0346	0.2464*
	(0.0236)	(0.1132)
Population growth	0.1942*	2.1663**
	(0.0893)	(0.6894)
Constant	0.7641***	9.5600***
	(0.0150)	(0.1266)
County fixed effects	YES	YES
State*Year fixed effects	YES	YES
Adj. R^2	0.7830	0.9784
N	18,626	18,593

Table 12 Interaction with Newspaper Coverage of Climate Change

This table presents the regression results of temperature anomaly on loan approval rate and amount, along with its interaction with newspaper coverage of climate change. The dependent variables are *Loan approval rate* in column 1 and *Ln(Loan amount)* in column 2. *Loan approval rate* is the ratio of the number of loan applications approved to the number of loan applications reviewed, and *Ln(Loan amount)* is the natural log of the amount of originated loans that are not sold to other institutions at the end of the year in a given county. The independent variable is *Temperature anomaly*, and its interaction with *Newspaper Coverage*. *Temperature anomaly* is the county-level 36-month average temperature anomaly. *Newspaper coverage* is the annual average newspaper coverage on climate change or global warming based on five US national newspapers including *Washington Post*, *Wall Street Journal*, *New York Times*, *USA Today*, and *Los Angeles Times* from Boykoff et al. (2019). The unit of analysis is at county-year level, and the sample period is from 2000 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at county and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Loan approval rate (1)	Ln(Loan amount) (2)
Temperature anomaly	0.0048	0.0175
	(0.0062)	(0.0487)
Temperature anomaly*Newspaper coverage	-0.0001**	-0.0002
	(0.0000)	(0.0002)
Loan-to-income	-0.0228***	0.0847**
	(0.0043)	(0.0355)
Income	0.0005***	0.0106***
	(0.0001)	(0.0006)
Fraction of minority applicants	-0.2570***	-0.6139***
	(0.0263)	(0.2019)
Employment growth	-0.0365	0.0079
	(0.0235)	(0.1040)
Wages growth	0.0514***	0.1409**
	(0.0143)	(0.0644)
Population growth	0.0855**	1.4777**
	(0.0348)	(0.6031)
Constant	0.7706***	9.3068***
	(0.0138)	(0.0898)
County fixed effects	YES	YES
State*Year fixed effects	YES	YES
Adj. R^2	0.7677	0.9700
N	52,768	52,653

Appendix A Variable Definitions

Variables	Definition
Climatic variables	
Temperature anomaly	Calculated as the difference between monthly temperature (in Fahrenheit degrees) and the historical (from 1961-1990) average temperature in a county. We then take a 36-month moving average of the temperature anomaly. A positive (negative) temperature anomaly means the recent 36-month local temperature is on average warmer (cooler) than the historical (from 1961- 1990) average temperature in that region.
Temperature anomaly_Quintile	A rank variable from 1 to 5, indicating the quintiles of *Temperature anomaly*.
Temperature anomaly_Q2-Q5	Dummies equal to one if a county belongs to the corresponding quintile of *Temperature anomaly*.
Borrowers and loan characteristics variables	
Loan approval rate	The ratio of the number of loan applications approved to the number of loan applications reviewed in a county-year.
Loan denial for collateral reason	The ratio of loan denials for the collateral reason among all loan denials in a county-year.
Loan denial for other reasons	The ratio of loan denials for other reasons among all loan denials in a county-year.
Ln(Loan amount)	The natural log of the amount of mortgage loans originated that are not sold to other institutions at the end of the year in a county.
Loan interest rate	The average fixed interest rate of loans at origination as indicated on the mortgage document in a zip code-year.
Default rate	The fraction of loans that become 90-days delinquent within 24 months since origination for loans approved in a zip code-year.
Loan-to-income	The average loan-to-income ratio for applications reviewed in a county-year.[41]
Income	The average borrower's total gross income for applications reviewed in a county-year, stated in thousands of US dollars per year.
Fraction of minority applicants	The ratio of the number of applications from minority applicants to the total number of applications reviewed in a county-year. Minority applicants include all applicants whose reported race is non-white.
Ln (# of applicants)	The natural log of the total number of mortgage applications reviewed in a county-year.
FICO	The classic FICO score developed by Fair Isaac Corporation to evaluate the quality of borrower creditworthiness. We average loan level FICO score to (3 digit) zip code-year level.
Loan-to-value	The average loan-to-value ratio at the time of mortgage origination in a zip code-year.
Loan term	The number of months in which regularly scheduled borrower payments are due under the terms of the related mortgage documents averaged to zip code-year level.
Macroeconomics variables	

[41] The definition in Table 4 is the average loan-to-income ratio in a zip code-year.

Employment growth	Annual percentage change in employment at county-year level.
Wages growth	Annual percentage change in wages at county-year level.
Population growth	Annual percentage change in population at county-year level.
HPI	House price index at county-year level.
Natural hazard damage	The nature logarithm of one plus the per capita damages due to natural hazards at county-year level. Natural hazards include floods, hurricane, tornado, storm and wildfire. The data is obtained from SHELDUS (Spatial Hazard Events and Losses Database for the United States).
Other Variables	
Worry	The fraction of population in a county who are somewhat/very worried about global warming from Yale Climate Opinions Maps.[42]
Timing	The fraction of population in a county who think global warming is already harming people in the United States now/within 10 years from Yale Climate Opinions Maps.
Sea-level rise	A dummy variable that equals to one if a county is exposed to sea-level rise risk according to Hallegatte et al. (2013), and zero otherwise.
Stern review	A dummy variable that equals to one if a year is within 3 years after the Stern Review was released (i.e., 2007, 2008 and 2009), and equal to zero if the year is within 3 years before the Stern Review was released (i.e. 2003, 2004 and 2005). The Stern Review was released on October 30, 2006.
Newspaper coverage	Average newspaper coverage on climate change or global warming topics based on 5 widely circulated national newspapers including *Washington Post*, *Wall Street Journal*, *New York Times*, *USA Today*, and *Los Angeles Times* from Boykoff et al. (2019).
Abnormal_SVI	The natural log of one plus the monthly Google search volume index (SVI) of the topic "Global warming" adjusted for seasonality.

[42] For *Worry* and *Timing* in Table B2. It is county-year panel data covers 2014-2018. Since the 2015 Yale Climate Opinion Maps is not available, we use the data in 2014 to supplement the data in 2015.

Appendix B
Table B1 The Persistence of Local Temperature Anomalies

This table reports the results on the persistence of local temperature anomalies. The dependent variable is *Temperature anomaly_ahead*, defined as the subsequent 36-month average temperature anomalies. The independent variable is *Temperature anomaly*, defined as the past 36-month average temperature anomalies. The unit of analysis is at county-year level, and the sample period is from 1990 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at county and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Temperature anomaly_ahead	
	(1)	(2)
Temperature anomaly	-0.1132	0.0596
	(0.1535)	(0.0596)
Constant	1.3644***	1.1785***
	(0.2508)	(0.0640)
County fixed effects	YES	YES
State*Year fixed effects	NO	YES
Adj. R2	0.0648	0.9471
N	83,408	83,408

Table B2 Temperature Anomaly and Mortgage Lending: Within-lender Analysis

This table presents the regression results of temperature anomaly on loan approval rate and loan amount at lender-county-year level. The dependent variables are *Loan approval rate* and *Ln(Loan amount)*. *Loan approval rate* is the ratio of the number of loan applications approved to the number of loan applications reviewed, and *Ln(Loan amount)* is the natural log of the amount of originated loans that are not sold to other institutions at the end of the year in a county. The independent variable *Temperature anomaly* is the county-level 36-month average temperature anomaly. A positive (negative) temperature anomaly represents a temperature warmer (cooler) than the 30-year (from 1961-1990) average. The unit of analysis is at lender-county-year level. Variable definitions are provided in Appendix A. Standard errors in parentheses are clustered at county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Loan approval rate (1)	Ln(Loan amount) (2)
Temperature anomaly	-0.0018***	-0.0270***
	(0.0003)	(0.0029)
Debt-to-income	-0.0201***	0.4675***
	(0.0002)	(0.0014)
Income	0.0003***	0.0034***
	(0.0000)	(0.0000)
Fraction of minority applicants	-0.0934***	-0.1763***
	(0.0005)	(0.0038)
Employment growth	-0.0000	-0.0021***
	(0.0001)	(0.0005)
Wages growth	0.0004***	0.0026***
	(0.0001)	(0.0004)
Population growth	0.1606***	1.4319***
	(0.0105)	(0.0801)
Constant	0.7630***	4.9229***
	(0.0006)	(0.0052)
County fixed effects	YES	YES
Lender*Year fixed effects	YES	YES
Adj. R^2	0.4086	0.4227
N	9,181,867	3,947,590

Table B3 Temperature Anomaly and the Characteristics of Loan Applicants

This table presents the regression results of temperature anomaly on the characteristics of loan applicants. The dependent variables are various characteristics of loan applicants including *Loan-to-income, Ln(income), Fraction of minority applicants* and *Ln(# of applicants)* at county-year level. The independent variable of interest is *Temperature anomaly*. *Temperature anomaly* is the county-level 36-month average temperature anomaly. A positive (negative) temperature anomaly represents a temperature warmer (cooler) than the 30-year (from 1961-1990) average. The unit of analysis is at county-year level, and the sample period is from 1990 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at county and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Loan-to-income	Ln(Income)	Fraction of minority applicants	Ln(# of applicants)
	(1)	(2)	(3)	(4)
Temperature anomaly	0.0155*	-0.0167***	0.0104*	0.0141
	(0.0077)	(0.0045)	(0.0051)	(0.0199)
Employment growth	-0.0392	-0.0255	0.0112	-0.3767*
	(0.0585)	(0.0180)	(0.0225)	(0.2020)
Wages growth	-0.1314**	0.0179	-0.0351*	0.1242
	(0.0518)	(0.0204)	(0.0177)	(0.1169)
Population growth	-0.1778	0.1328	-0.0752	0.6100**
	(0.1170)	(0.0781)	(0.0482)	(0.2495)
Constant	1.6621***	4.0910***	0.2145***	6.4477***
	(0.0076)	(0.0047)	(0.0056)	(0.0208)
County fixed effects	YES	YES	YES	YES
State*Year fixed effects	YES	YES	YES	YES
Adj. R^2	0.7892	0.8709	0.7960	0.9543
N	83,408	83,408	83,408	83,408

Table B4 Using Indirect Climate Disasters as an Alternative Proxy of Climate Change Belief

This table presents the regression result of indirect climate disasters on the mortgage origination. The dependent variables are *Loan approval rate* and *Ln (Loan amount)*. The independent variable of interest, *Indirect climate disasters,* is defined as the number of neighboring counties that experience the climate change-related disasters for each county in a year. Climate change-related disasters include hurricanes, flooding, and wildfire. The unit of analysis is county-year level, and the sample period is from 1990 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are clustered at county level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Loan approval rate (1)	Ln(Loan amount) (2)
Indirect climate disasters	-0.002**	-0.018**
	(0.001)	(0.007)
Loan-to-income	0.001	0.231***
	(0.003)	(0.026)
Income	0.001***	0.011***
	(0.000)	(0.001)
Fraction of minority applicants	-0.225***	-1.745***
	(0.013)	(0.096)
Employment growth	-0.044**	-0.341**
	(0.022)	(0.169)
Wages growth	0.040***	0.141
	(0.016)	(0.123)
Population growth	0.035	1.017***
	(0.033)	(0.275)
Constant	0.678***	8.887***
	(0.008)	(0.065)
County fixed effects	YES	YES
State*Year fixed effects	YES	YES
Adj. R2	0.6373	0.9267
N	44,632	43,661

Table B5 Temperature Anomaly and Loan Approval Rate and Amount: Robustness Tests

This table presents several robustness tests. Panel A shows the baseline results using the sample of counties that experienced above average growth in the number of mortgage applicants. Panel B reports results using the sample of counties that experienced above average growth in the total amount of mortgages applied. Panel C includes county-level house price index (HPI) as an additional control variable. Panel D excludes the house price bust and subprime mortgage crisis period (year 2006 to 2010) from the sample. Panel E controls damage caused by natural disasters in the county-year. Panel F excludes five states (i.e., California, Florida, Louisiana, New Jersey and Texas) that jointly account for nearly 70% of National Flood Insurance Program policies. The dependent variables for all panels are *Loan approval rate* and *Ln (Loan amount)*. The independent variable is *Temperature anomaly*. The unit of analysis is county-year level, and the sample period is from 1990 to 2016. Variable definitions are provided in Appendix A. Standard errors in parentheses are two-way clustered at county and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Panel A		Panel B		Panel C	
	Loan approval rate	Ln(Loan amount)	Loan approval rate	Ln(Loan amount)	Loan approval rate	Ln(Loan amount)
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature anomaly_Q5	-0.0086**	-0.0866**	-0.0095**	-0.0727*	-0.0087***	-0.0625**
	(0.0032)	(0.0317)	(0.0037)	(0.0358)	(0.0021)	(0.0277)
Temperature anomaly_Q4	-0.0065*	-0.0649**	-0.0072**	-0.0600**	-0.0061***	-0.0321
	(0.0032)	(0.0240)	(0.0033)	(0.0255)	(0.0019)	(0.0211)
Temperature anomaly_Q3	-0.0030	-0.0435**	-0.0039	-0.0401*	-0.0036**	-0.0185
	(0.0024)	(0.0204)	(0.0027)	(0.0203)	(0.0016)	(0.0179)
Temperature anomaly_Q2	-0.0032	-0.0265	-0.0038*	-0.0259*	-0.0016	-0.0018
	(0.0023)	(0.0165)	(0.0022)	(0.0145)	(0.0014)	(0.0140)
HPI					-0.0000	-0.0014*
					(0.0000)	(0.0007)
Constant	0.7005***	8.8526***	0.7031***	8.9378***	0.7427***	9.9530***
	(0.0209)	(0.1864)	(0.0179)	(0.2053)	(0.0176)	(0.3249)
Mortgage applicants' characteristics controls	YES	YES	YES	YES	YES	YES
Macroeconomics controls	YES	YES	YES	YES	YES	YES
County fixed effects	YES	YES	YES	YES	YES	YES
State*Year fixed effects	YES	YES	YES	YES	YES	YES
Adj. R2	0.6712	0.9343	0.6666	0.9300	0.7598	0.9148
N	40,055	39,602	40,063	39,576	64,954	64,825