Climate Change, the Partisan Divide, and Exposure to Climate Risk

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Abstract

I study how partisan-driven beliefs about climate change affect the distribution of climate risk across mortgage lenders. Using wildfires to capture climate exposure, I find that Republican-leaning lenders are more likely to approve mortgage applications in high wildfire risk areas than Democratic-leaning lenders. This difference in approval rates is only evident among second-lien and jumbo mortgage applications, highlighting how securitization affects risk-taking incentives. Lastly, Republican-leaning lenders originate more climate-exposed second-lien and jumbo loans and thus hold more wildfire risk. The findings suggest that dispersion over climate change beliefs affects how institutional investors hold climate risks, potentially affecting financial stability.

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1 Introduction

Expectations about climate risk can affect investment decisions. Investors who are more concerned about climate change may view climate-change-exposed assets, such as those exposed to wildfire risk, as expensive and thus negative NPV. However, more optimistic investors can view the same assets as profitable. Disagreement over climate risks can thus lead to self-sorting among institutional investors in holding climate risk. While many papers study how climate risk is priced in the financial market, there is little evidence on the distribution of climate risk in the financial system, which has important implications for understanding how climate change could affect the stability of the financial system (Giglio et al., 2021).[1] This paper attempts to fill this gap.

I study the mortgage market and find that the partisan divide over climate risk expectations affects lenders' investment decisions. Partisan identity has been shown to correlate with many dimensions of investor beliefs, including those about climate change.[2] In fact, studies show that Republicans are more optimistic and less concerned about climate change than Democrats (Dunlap et al., 2016; Baldauf et al., 2020). Similarly, surveys find an increasing partisan divide on the climate change issue (see Figure 1). Thus, I use mortgage lenders' political preferences — as measured by the fraction of political contributions from their political action committees (PACs) to Republican politicians (*REP Donation%* henceforth) — to capture their optimism about climate risk.[3] I find that Republican-leaning lenders are more likely to approve mortgage applications in high wildfire risk areas. These effects only exist among high-risk second-lien mortgages and hard-to-securitize jumbo mortgage applications. Republican-leaning lenders also receive more mortgage applications and originate more mortgage loans than Democratic-leaning lenders in high fire risk areas, suggesting that financial institutions with more optimistic views about climate change hold more climate-change-exposed assets in their investment portfolios.

[1]Swiss Re Group, the world's largest reinsurance company, estimates that by 2050, climate change will cost approximately 10% of the world's total economic value if it stays on the currently-anticipated trajectory.

[2]See, e.g., Gerber and Huber (2009), Cookson et al. (2020), and Allcott et al. (2020).

[3]To validate the *REP Donation%* measurement, I rely on the firm-level climate change exposure constructed by Sautner et al. (2020) and find that Republican lenders are indeed less likely to mention climate risk and express more positive sentiment about climate change on conference calls.

The primary empirical challenge is to measure climate risk. Some studies rely on historical natural disasters to make inferences about future climate risks. Historical disasters, however, do not necessarily predict future risks.[4] Moreover, not all adverse weather events can be directly attributed to climate change. In this paper, I use the Wildfire Hazard Potential (WHP) map, obtained from the U.S. Forest Service, to construct a forward-looking wildfire hazard measurement. The WHP map depicts the potential for future wildfires that would be difficult to contain in the continental United States. When combined with the locations of mortgages' underlying properties, the map provides direct estimations on mortgages' exposure to wildfire risk.

Several features make wildfire risk an appealing representation of climate risk. First, the relationship between climate change and wildfires is straightforward: global warming increases heat and creates drier conditions, making it easier for wildfires to spread and harder for them to be contained. Figure 2 shows that the correlation between wildfires and global temperature anomaly reaches approximately 60%.[5] Second, both the threat of wildfires and the losses incurred by those wildfires have continued to grow.[6] As shown in Figure 2, the number of acres burned in the United States has increased fivefold over the last 40 years, reaching 10 million acres in 2020 (twice the land area of Massachusetts).[7] CoreLogic, a property intelligence company, estimates that, nationwide, more than $638 billion worth of single-family residences are at risk from wildfires. Third, wildfires represents one of the least insured natural disasters - insurance companies sometimes cancel existing policies and charge higher premiums in fire-prone regions.[8] In addition, Issler et al. (2020) show that mortgage delinquency rate increases

[4]Ramsay (2017) shows that a remarkably consistent number of tropical cyclones (both hurricanes and tornadoes) are formed each year, indicating a less-decisive relationship between climate change and the formation of tropical cyclones. For similar discussions, see "What We Know About Climate Change and Hurricanes," *The New York Times*, August 29, 2021.

[5]The data on wildfire acres is obtained from the National Interagency Fire Center, and the data on global temperature anomaly is taken from the National Oceanic and Atmospheric Administration.

[6]The estimated total loss from the 2018 California wildfires alone reached approximately $150 billion, Wang et al. (2021). As a result of the 2018 California wildfires, Merced Property & Casualty Co, an insurance company, and Pacific Gas & Electric Corp., California's largest utility company, both filed for bankruptcy

[7]Internationally, we also saw more wildfires burning in Australia, Canada, Greece, Turkey, the Amazon rainforest, and even Siberia.

[8]See ""Insurers dropped nearly 350,000 California homeowners with wildfire risk", *The Sacramento Bee*, August 20, 2019; "Many Californians Being Left Without Homeowners Insurance Due to Wildfire Risk", *Insurance Journal*, December 4, 2020.

significantly after exposures to wildfires. Fourth, wildfires pose more immediate threats to the economy. Conversely, the impacts of other types of climate change, such as sea-level rise, will take decades to be fully realized.

In the main analysis, I estimate regressions by interacting *REP Donation%* with mortgage applications' exposure to wildfire risk. Lenders' mortgage issuance decisions depend on a variety of factors, such as borrowers' credit risk, local economic conditions, etc.[9] For identification, I first control for time-varying local economic conditions (e.g., employment rate, real estate price, mortgage demand) by including county-year fixed effects. Moreover, the time-invariant unobserved heterogeneities (e.g., loan officer leniency, local enrollments in higher education) across lender branches can also impact lenders' mortgage issuances decisions. Therefore, I further control for lender-county fixed effects. Lastly, I control for a battery of loan and borrower characteristics. The empirical strategy thus compares mortgage issuance decisions by lenders with different climate-risk beliefs in the same county and year, while at the same time controlling for borrower characteristics, loan characteristics, and fixed differences between lender-county pairs. Furthermore, I conduct alternative analyses based on staggered difference-in-differences tests using historical wildfires as natural experiments.

My first key finding is that Republican-leaning lenders have a significantly higher approval rate of the mortgage applications than Democratic-leaning lenders in high wildfire risk areas. Importantly, the difference in mortgage approval rates only exists among mortgage applications that are less securitizable after originations (second-lien or jumbo), indicating that lenders have little incentive to price climate risk for mortgages that won't stay in their portfolios. The effects are also economically sizable. Compared with low fire risk areas (25th percentile), a one-standard-deviation increase in *REP Donation%* in high fire risk areas leads to an approximately 3.44% (0.47%) higher approval rate of second-lien (jumbo) mortgage applications in high wildfire risk areas (75th percentile). On the contrary, in low-risk areas, a one-standard-deviation increase in *REP Donation%* is associated with statistically insignificant changes in mortgage approval rates. Moreover, the effects are larger for areas exposed to higher fire risk (i.e., those in the 80th or 90th percentile).

[9] Studies also find that local real estate markets depend on residents' beliefs about climate change (Baldauf et al., 2020; Bernstein et al., 2020).

The findings help to rule out several alternative explanations. First, mortgage lenders' mortgage approval decisions might depend on their partisan perception of economic outlooks (Kempf and Tsoutsoura, 2021; Dagostino et al., 2020). This explanation is unlikely because it does not explain the statistically insignificant results in low wildfire risk areas. The second alternative explanation is a political favor story: Republican-leaning lenders might be connected with Republican politicians, and these lenders might approve more mortgage applications in Republican-leaning electoral areas to help Republican incumbents get re-elected, as found in Bertrand et al. (2018). This is also unlikely, because wildfire risk is not distributed in a partisan way. Moreover, I split the sample based on counties' Republican vote share in the 2012 presidential election and show that the effects exist in both "red" and "blue" regions. The third alternative story is related to lenders' general risk tolerance. Lenders may have exactly the same climate risk perceptions, but Republican-leaning lenders may have a higher risk tolerance and thus are more willing to invest in risky assets. I examine lenders' general risk tolerance, and the findings suggest that this explanation does not hold. To further support the climate risk belief interpretation, I provide two additional pieces of evidence. Republican-leaning lenders are more likely to hold mortgage loans originated in fire-prone areas, and they are also less likely to deny mortgage applications for collateral-related reasons, indicating that Republican-leaning lenders are more optimistic towards mortgage underlying properties exposed to fire risk.

I proceed to show that Republican-leaning lenders' more optimistic lending policies bring them more mortgage applications in high wildfire risk areas. Even if mortgage applications exposed to high fire risks are rejected by Democratic-leaning lenders, borrowers can still file mortgage applications with Republican-leaning lenders.[10] As a result, Republican-leaning lenders receive more mortgage applications in high fire risk areas. Indeed, I find that although lenders charge similar interest rates, Republican-leaning lenders receive a higher number of mortgage applications in high fire risk areas than Democratic-leaning lenders. Compared with low-risk areas (25th percentile), a one-standard-deviation increase in *REP Donation%* is associated with an approximately 5.72% (2.15%) increase in the number of second-lien (jumbo) mortgage applications from high wildfire risk areas (75th percentile).

These findings show that in high wildfire risk areas, optimistic Republican-leaning lenders

[10] More optimistic Republican-leaning lenders may also advertise more in high wildfire risk areas.

not only have a higher approval rate but also receive more mortgage applications than pessimistic Democratic-leaning lenders. Taken together, these two findings suggest that Republican-leaning lenders originate more mortgages in the high wildfire risk areas. Further tests confirm this point. Relative to low wildfire risk areas (25th percentile), a one-standard-deviation increase in *REP Donation%* is associated with a 9.3% (2.9%) higher total amount of originated second-lien (jumbo) mortgages in high wildfire risk counties (75th percentile), highlighting that optimistic lenders hold more wildfire risks in their portfolio. The effects remain insignificant in low fire risk areas. In dollar terms, a one-standard-deviation increase in lenders' *REP Donation%* is associated with a $178 million approximate increase in their nationwide originations and holdings of second-lien and jumbo mortgages.

Given that the true risk parameters of wildfires are unknown, it's almost impossible for one to find the ex-ante optimal lending policies. The lack of data on loan performance of second-lien and jumbo loans represents another limitation. In this paper, I rely on the single-family loan performance data from Fannie Mae and Freddie Mac to examine the delinquency rates of mortgages after wildfires. Since the data only covers conforming loans, it's unlikely that any difference will be found in delinquency rates between mortgages originated by Republican-leaning and Democratic-leaning lenders after wildfire incidents. Indeed, the findings using single-family loan performance data confirm this point. Similar to Issler et al. (2020), the delinquency test does show that mortgage delinquency rates increase significantly after wildfires. Therefore, it can be inferred that Republican-leaning lenders bear more losses after wildfires since they originate more second-lien and jumbo loans in high wildfire risk areas. Again, due to data limitations, the short-term trade-off between benefits from a higher market share and the costs from higher mortgage defaults is unclear. Lastly, large-scale wildfires represent tail risks, and wildfires are expected to accelerate with greater severity in the future. The likelihood of tail events also changes depending on how climate change evolves. In other words, the current optimal lending policy won't be the same as the long-term optimal lending policy.

This study is, to the best of my knowledge, the first to identify how the disagreement over climate risk beliefs lead to self-sorting among institutional investors in holding climate-exposed assets. Many empirical studies in the climate finance literature focus on documenting how climate risk is priced in the financial market while treating financial investors with homogenous climate risk concerns.[11] However, survey evidence (Ilhan et al., 2020; Stroebel and Wurgler, 2021; Bresnahan et al., 2021) shows sizable dispersions among financial investors. My study explores the heterogeneity of financial investors' climate risk beliefs and identifies who are more likely to hold climate risks. As pointed out by Giglio et al. (2021), understanding the distribution of climate risks among market participants is "an important and valuable research agenda" because it not only helps institutions to manage and hedge their own climate risk exposure but also helps regulators to ensure that climate change will not become a systematic threat to the financial stability.

This paper also adds to the recent literature studying how partisan divide in climate change belief affects individual economic decisions. Baldauf et al. (2020) study the role of climate change beliefs in real estate markets, finding that houses exposed to sea-level rise in Democratic-leaning areas sell for less money than similar houses in Republican-leaning areas. Relatively, Bernstein et al. (2020) show that partisan beliefs in climate change are reflected in households' residential choices, with Republicans more likely to own coastal properties. Ratnadiwakara and Venugopal (2020) find that partisan climate risk perception also influences individuals' demand for flood insurance. I contribute to the literature by focusing on financial institutions and the supply side of the mortgage market and extending the role of partisan climate risk perceptions from household decision making to institutional decision making.

Finally, my paper provides methodological contributions to the climate finance literature. One popular measurement of climate risk in the literature is sea-level rise. The wildfire risk measure based on the Wildfire Hazard Map has a couple of advantages over the sea-level rise risk measure. As discussed earlier, the wildfire risk represents a more immediate threat from climate change than sea-level rise. Many short maturity asset classes that are hardly impacted by sea-level rise, such as business loans, are subject to wildfire threats. Moreover, sea-level rise, by nature, mostly impacts coastal areas and the corresponding real estate and mortgage markets. On the contrary, wildfire risks exist in both coastal and inland regions. Thus, one can measure wildfire risks for businesses, municipalities, and agriculture, etc.

The rest of the paper proceeds as follows. Section 2 describes the institutional background

[11] See, e.g., Goldsmith-Pinkham et al. (2019), Correa et al. (2020), Duan and Li (2021), and Painter (2020).

and develops hypotheses. Section 3 describes the data. Section 4 presents empirical estimations on mortgage approval rates. Section 5 studies whether more optimistic lenders hold more climate risk. Section 6 provides further analysis on real effects, other types of climate risks, and a battery of robustness tests. Section 7 concludes the paper.

2 Hypothesis Development

The mortgage market is an ideal setting to study how physical climate risk is distributed in the financial system. First, mortgage loans are standardized financial investments that are highly comparable across mortgage lenders. In fact, sometimes one mortgage applicant sends the same mortgage application to multiple lenders. Second, lenders originate mortgage loans in all 50 states. Locations of the underlying properties provide a direct estimation of mortgages' exposure to physical climate risks. Third, the long maturity of mortgage loans (typically 30 years) is another advantage because the long-term effects of climate change (i.e., sea-level rise) take time to be fully realized. Lastly, in the mortgage application process, mortgage lenders' underwriting departments typically make the final decisions on whether to approve mortgage applications.[12] In other words, the final mortgage approval decisions are centralized at the firm level, making it legitimate to measure corporate climate change beliefs at the mortgage lender level.

Many lenders have been increasingly taking climate change into account as a risk factor (see Table A.3 for anecdotal evidence from the SEC filings).[13] Moreover, studies (e.g., Dunlap et al., 2016; Baldauf et al., 2020) and survey evidence (see Figure 1) show that Republican-leaning individuals are more optimistic about climate change. Taken together, I argue that Republican-leaning lenders and Democratic-leaning lenders have diverse perceptions of climate change and potentially price climate risk differently when reviewing mortgage applications. Importantly, I do not assume that Republican-leaning and Democratic-leaning lenders behave binarily on incorporating climate risk in their lending process, which is unlikely to be the case. Instead, I only assume that lenders apply different weights of climate risk in their internal risk models.

[12]See "The Mortgage Underwriting Process Explained," Merchants Bank.

[13]Recent studies also show the impacts of climate change on lenders' mortgage business (see, e.g., Nguyen et al., 2020; Ouazad and Kahn, 2019; Duan and Li, 2021).

Given these analyses, I reach my first hypothesis.

Hypothesis 1: *In areas exposed to high climate risk, Republican-leaning lenders are more likely to approve mortgage applications than Democratic-leaning lenders.*

It is well understood that securitization reduces mortgage lenders' incentive to screen borrowers (Keys et al., 2010). Through the same reasoning, securitization can also reduce lenders' incentive to consider climate risk. Two main factors—the loan amount and lien status—influence the securitization process. Jumbo loans, which are loans that exceed the conforming loan limits, are not eligible to be purchased by Fannie Mae or Freddie Mac, making these loans hard to securitize. Second-lien mortgages are also less likely to be securitized due to their high-risk nature (Lee et al., 2013). As a result, both second-lien and jumbo mortgage loans are highly likely to remain in lenders' investment portfolios after origination. Therefore, it's expected that mortgage lenders are more likely to consider climate risk among second-lien and jumbo mortgage applications but not among the conforming mortgage applications, making the effects less significant among conforming mortgage applications.

Hypothesis 2: *The difference in the approval rates of mortgage applications between Republican-leaning and Democrat-leaning lenders decreases with the securitibility of mortgages: (1), whether the mortgage is a section-lien secured; (2), whether the mortgage is a jumbo loan.*

The difference in mortgage approval rates can also have an impact on the demand side. From a borrower's prospective, their demand for mortgage loans won't disappear if their initial mortgage application is denied by one bank. If Democratic-leaning lenders are less likely to approve mortgage applications in high climate risk areas, the mortgage borrowers in these areas can submit new applications and borrow from more climate-optimistic Republican-leaning lenders. Moreover, relative to climate-pessimistic mortgage lenders, optimistic lenders may advertise more in high climate risk regions. Consequently, thanks to their higher tolerance of climate risks, Republican-leaning lenders can receive a higher number of mortgage applications in high climate risk areas. Given the higher approval rate and higher number of applications, it's expected that Republican-leaning lenders issue more mortgages in high risk areas.

Hypothesis 3: *Thanks to their high tolerance for climate risk, Republican-leaning lenders receive a* *higher number of mortgage applications and also originate more mortgage loans in high climate risk areas.*

The effects of climate change take various forms, including sea-level rise, flooding, wildfire, abnormal temperature, etc. However, not all climate change effects will be priced in the same way by mortgage lenders. In the context of mortgage lending, wildfire risk potentially represents the most prominent climate risk. The primary reason is the lack of insurance coverage. Insurance for wildfires is mostly provided by commercial insurance companies. In fact, while wildfires are becoming increasingly severe, the insurance market for wildfires has shrunk.[14] Insurance providers often charge high insurance premiums and refuse to renew insurance policies in high wildfire risk regions.[15] Along with high repair costs after wildfires, the mortgage default rate after wildfires is very high (Issler et al., 2020).[16] In comparison, the National Flood Insurance Program provides insurance protections for flooding in most areas of the United States, even after major hurricanes (Kousky et al., 2020). As for sea-level rise, the long-term effects take decades to be realized. The short-term effects of sea-level rise, such as floods, are also protected by insurance programs such as the National Flood Insurance Program.

Hypothesis 4: *Compared to climate risks such as flood and sea level rise, the difference in the probability of approving mortgage applications is stronger with wildfire risk.*

3 Data and Sample Construction

This paper combines data from various sources, including: (1) Home Mortgage Disclosure Act (HMDA) mortgage application data; (2) the Wildfire Hazard Potential map from the United States Forest Service (USFS); (3) campaign finance data from the Federal Election Commission (FEC); (4) the single-family loan performance data from Fannie Mae and Freddie Mac; (5)

[14] See "As US wildfire threat grows, insurance capacity shrinks," *S&P Global Market Intelligence*, 21 July 2021.

[15] See "As wildfire risk increases in Colorado and the West, home insurance grows harder to find," *The Denver Post*, January 7, 2019; "Many Californians Being Left Without Homeowners Insurance Due to Wildfire Risk," *Insurance Journal*, December 4, 2020.

[16] According to American Family Insurance, while a small in-house fire costs between $3,000 and $5,000 to repair, repairing the damage from large fires can cost $50,000 or more. In comparison, according to the HomeAdvisor, the typical range of repairing water-damaged houses is between $1,200 and $5,000.

Historic Fire Perimeters data from the National Interagency Coordination Center (NIFC); (6) national flood hazard layer data from the Federal Emergency Management Agency (FEMA); (7) sea-level rise data from the National Oceanic and Atmospheric Administration (NOAA); (8) real estate price data from the Zillow Home Value Index (ZHVI); and (9) regional economic accounts data from the U.S. Bureau of Economic Analysis (BEA). The following subsections describe several main data in detail.

3.1. Mortgage Related Data

I obtain mortgage application information from the publicly-available HMDA data. The public version of the HMDA data provides an annual summary of mortgage applications. The data provides various types of information, including borrower, loan, lender, and property characteristics. Borrower characteristics include ethnicity, race, gender, and gross income. Loan characteristics include the amount of the loan, loan type, lien status, approval decision, denial reason, and whether an originated loan is securitized in the secondary market. Property characteristics mainly cover information about the property's location, such as state, county, and census tract.

I apply two filters during the sample construction. First, I only include conventional mortgage applications. Thus, loan applications insured by government agencies, such as the Federal Housing Administration and Veterans Administration, are excluded from the sample.[17] Second, I include loan applications with the type of action from 1 to 3. By applying this filter, I exclude mortgage applications that are either incomplete or withdrawn by applicants. This filter also excludes mortgages purchased by financial institutions to avoid the double counting of mortgage loans (where *type_of_action* equals 6). A small number of preapproval mortgage applications are also not included in the sample. This is because lenders only voluntarily report preapproval mortgage applications.[18]

Two changes in the HMDA 2018 reporting policies impact my analysis. First, under the new

[17] The mortgage applications that are insured by government agencies account for approximately 25% of all mortgage applications.

[18] The second filter drops about 30% of the remaining mortgage applications (among the 30%, about 20% of mortgages are purchased by financial institutions, about 8%-9% of mortgage applications are incomplete or withdrawn, and the remaining 1% of them are preapproval-related applications).

reporting policy, most lenders are required to report home equity lines of credit (HELOCs).[19] The change has a significant impact on the number of second-lien mortgage applications reported by lenders. Under the pre-2018 regulation, some lenders choose not to report second-lien mortgage applications that are HELOCs. For example, JPMorgan Chase reported 43 second-lien mortgage applications in 2017 and 112,845 second-lien mortgage applications in 2018. For Bank of America, the numbers are 32 and 194,279, respectively. To ensure that lenders consistently report the second-lien mortgage applications, I drop lenders from the second-lien mortgage application sample if a lender has fewer than 1,000 applications in any year from 2012 to 2019.[20] Second, a new variable classifying whether a mortgage application passes conforming loan limits was added in the 2018 and 2019 HMDA data. Following the literature, I rely on the loan amount and county-level conforming loan limits to identify jumbo loans for mortgage applications before 2018. For the 2018 and 2019 mortgage applications, I rely on the new variable to identify jumbo loans.[21]

In addition to the HMDA mortgage application data, I obtain the mortgage performance and the mortgage interest rate data of conforming loans from the Fannie Mae and Freddie Mac Single-Family loan performance database. The data track the loan performance over the lifecycle of conforming loans and provide a variety of borrower and loan characteristics. Loan characteristics include origination month, origination interest rate, original loan to value, and seller information. Borrower characteristics provide information on borrowers' credit scores and debt-to-income ratios. The loan performance information also includes monthly delinquent information.

3.2. Measuring Climate Risk Beliefs Using Lenders' Political Donations

I capture lenders' climate risk beliefs based on their political preferences. Following the literature, I measure lenders' political preferences using political donations made by their

[19]See "CFPB finalizes temporary increase of HMDA HELOC reporting threshold and other minor HMDA amendments," *Ballard CFS Group*, August 25, 2017.

[20]The results are similar without this filter.

[21]The distributions of jumbo loans are similar before 2018 and after 2018.

corporate Political Action Committees (PACs) to federal candidates.[22] The federal political donation data are taken from the Federal Election Commission (FEC).

It is worthwhile to describe how corporate PACs make political donations based on the behavior of corporations. Under the current Federal Campaign Finance Law (2 U.S.C. § 441b), corporate PACs can only solicit voluntary political contributions from employees, shareholders, and family members of these two groups. Corporations often create internal committees chaired by senior managers to oversee PAC activities.[23] In sum, corporate PACs collect funds from employees and related stakeholders and then make political donations with corporate leaders' influence.

To identify lenders' PAC contributions, I match all PACs of *corporation* organization type (FEC ORG_TP: C) with mortgage lenders from the HMDA data. In total, there are over 8000 mortgage lenders in the HMDA data. However, the largest 500 mortgage lenders receive over 80% of all mortgage applications. I match the top 500 mortgage lenders with corporate PACs from the FEC data. Not all 500 lenders have corporate PACs, and the final matched sample includes 84 mortgage lenders. The 84 mortgage lenders include banks, retail mortgage lenders (i.e., Quicken loans), and federal credit unions. The 84 lenders are also geographically dispersed and headquartered in about 30 states.

I calculate the fraction of corporate political contributions donated to Republican politicians over the last two election cycles (4 years) to measure firms' political preferences. On the one hand, a short time window, such as one or two years, is likely to represent lenders' policy preferences, which introduce irrelevant noise. On the other hand, measurements based on a long time window, such as 6 to 10 years, do not consider changes in lenders' political preferences.[24] Specifically, I first calculate the total direct contribution made by a lender's corporate PAC to all federal candidates in the last four years. Then, I calculate the mortgage lender's PAC contribution to all Republican candidates in the last four years. Finally, I calculate

[22] Corporate PAC contributions are widely used in the literature to identify corporate political connections and political preference (see, e.g., Cooper et al., 2010; Akey, 2015; Di Giuli and Kostovetsky, 2014; and Kempf et al., 2021).

[23] "The 2019 CPA-Zicklin Index Corporate Political Disclosure and Accountability" report from the Center for Political Accountability shows that nearly half of S&P 500 companies have board oversight of corporate PAC activities.

[24] The results hold robust to alternative specifications of years, such as three years or five years. I provide robustness tests in the robustness section.

the main explanatory variable *REP Donation%* as follows. Figure A.1 presents the sample distribution of the *REP Donation%*.

$$REPDonation\% = \frac{Total\ Donations\ to\ REP\ Candidates}{Total\ Donations\ to\ ALL\ Candidates} \tag{1}$$

One potential concern is about the extreme value of the *REP Donation%* due to less active PAC donations. For example, if a company donates only $200 in a year, it is likely that it donated all $200 to one candidate. Thus, the company will be identified as 100% Republican or 100% Democrat with the *REP Donation%* equaling either 0 or 1. However, it may be that the company is simply less active in making political contributions. To alleviate this issue, I drop lender-year pairs if a lender has made donations worth less than $10,000 over the last four years.[25]

There are several advantages to measuring mortgage lenders' political preferences using corporate PAC campaign contributions. Most corporate PACs make political donations consistently over time, while contributions made by CEOs are relatively sparse. On the contrary, employee contributions can be more populated than PAC contributions but do not reflect the structure of decision making within companies as PAC contributions do. Moreover, comparing the PAC contributions with voter registration data, which classifies individuals into Republican and Democrat politicians, enables me to identify mortgage lenders' political preference on the political spectrum from fully conservative to fully liberal.

3.3. Wildfire Hazard

I rely on the Wildfire Hazard Potential (WHP) map from the U.S. Forest Service (USFS) to measure wildfire risk; see Figure 3 for the 2018 WHP map (Dillon, 2015). The WHP map quantifies wildfire risk based on various types of information, including weather, historical fire occurrence, terrain, spatial fuel, and vegetation coverage.[26] The map has two forms: continuous integer values and classified values. The evaluation of wildfire risk in the continuous WHP map takes integer values from 0 to 100,000. In the classified WHP map, wildfire risk is classified

[25]The findings are not sensitive to this filter, and I provide robustness analysis in the robustness section.

[26]See "FSim-Wildfire Risk Simulation Software," U.S. Forest Service; "Wildfire Hazard Potential," U.S. Forest Service.

into five categories, including very low, low, moderate, high, and very high.

In my analysis, I construct county-level wildfire risk measurements based on both the continuous and the classified WHP map. Based on the continuous version of the WHP map, I construct the continuous wildfire risk measurement as the log of the average value of wildfire hazard within a county, *Log(WFH)*. Additionally, I construct two classified county-level wildfire risk measurements: *High Risk* and *VHigh Risk*. *High Risk* measures the fraction of lands that are assigned as high risk or very high risk within a county, and *VHigh Risk* measures the fraction of lands that are assigned as very high within a county.

There are a couple of limitations related to the WHP map. USFS has published several WHP maps, including the 2012 version, the 2014 version, and the 2018 version. For each year without the WHP map, I assume it has the same value as the last available map. To illustrate, the wildfire risk in 2013 is the same as the risk in 2012. Since the earliest WHP map available is from 2012, my sample period starts from 2012. In addition, the WHP maps only cover the continental United States. States like Alaska and Hawaii are not included in the analysis.

3.4. Sea-Level Rise and Flood Risk

To measure county-level sea-level rise (SLR) risk, I obtain sea-level rise data from the National Oceanic and Atmospheric Administration (NOAA). NOAA's SLR data estimate areas that will be submerged into the sea if the sea level rises by 0 to 10 feet. To capture sea-level rise exposure, I calculate county-level sea-level rise risk measurements based on the fraction of areas that are impacted if the sea level rises by 5 feet – *SLR 5 Feet%*.

I measure flood risk based on the flood hazard map obtained from the Federal Emergency Management Agency (FEMA). Consistent with the measurement of wildfire risk, I calculate a county-level flooding risk based on the percentage of high flooding areas within a county, *High Risk (Flood)*. The FEMA flood hazard map assigns local communities with different designations of flood hazards, including Zone A, Zone AE, Zone B, Zone V, etc. For example, Zone A represents areas with a 1% annual chance of flooding and a 26% chance of flooding over the life of a 30-year mortgage. Following FEMA's classification, I attribute flood zones that begin with the letters A and V as high-risk areas and attribute flood zones that begin with the letters

B, C, and X as moderate and low-risk areas.[27]

3.5. Summary Statistics

Table 1 presents the summary statistics of the full HMDA mortgage application sample. The sample period is from 2012 to 2019. The sample period starts from 2012 because the first wildfire hazard map was published in 2012. Starting from 2020, the Covid-19 pandemic caused both a global health crisis and a global economic recession. Thus, my sample stops at 2019 to avoid the potential impact from the pandemic. In total, the sample includes 24,771,654 mortgage applications to 84 lenders from 3,108 counties. While 84 lenders seems to be a small number, the lenders' 24,771,654 mortgage applications represent 36.44% of all mortgage applications during the sample period, indicating a large sample. Panel A presents the summary statistics of the second-lien and non-jumbo sample. Panel B presents the summary statistics of the jumbo and first-lien sample. Panel C presents the summary statistics of the non-jumbo and first-lien sample. In the paper, I conduct estimations based on multiple samples, and I provide summary stats of these samples in the online appendix.

4 Mortgage Approval Rate

In this section, I present empirical results on whether lenders' climate-risk beliefs impact their mortgage approval decisions. The first subsection describes the empirical strategy in detail. I next present the key findings based on the empirical strategy. Then, I present further evidence to separate the climate change belief channel with alternative explanations. Lastly, I conduct a "staggered difference-in-differences" analysis using historical wildfire incidents as natural experiments.

4.1. Empirical Strategy on Mortgage Approval Decisions

In the baseline empirical analysis, I test *Hypothesis 1* on whether the partisan divide in climate-risk beliefs affects lenders' mortgage approval decisions in high climate risk areas. Formally, I

[27] See the definitions of FEMA Flood Zone Designations on the FEMA website.

estimate the following interaction model:

$$Approval_{i,b,c,t} = \alpha_{c,t} + \lambda_{b,c} + \beta_1 \times REP\ Donation\%_{b,t} + \beta_2 \times REP\ Donation\%_{b,t} \times Climate\ Risk_{c,t} + \theta' Controls_{i,b,c,t} + \epsilon_{i,b,c,t} \tag{2}$$

The sample is at the application level. *Approval* is an indicator variable on the final approval decision of mortgage application i received by lender *b* in county *c* in year *t*. Two main explanatory variables include the measurement of lenders' political preference, *REP Donation%*, and measurement of climate risk, *Climate Risk*. As described in the previous section, *REP Donation%* represents the fraction of total corporate PAC donations to Republican politicians from *t-5* to *t-1*. Climate Risk measurements include *Log(WFH)*, *High Risk*, and *VHigh Risk*. *Log(WFH)* is the wildfire risk measurement based on the continuous version of the WHP map. *High Risk* (*VHigh Risk*) measures the fraction of lands that are identified as high or very high (very high) risk in the classified version of the WHP map. The *Controls* variable represents control variables, including Log(Loan Amount), Income, Gender, Race, and Log(#Tot Lender Applications).[28] Appendix Table A.1 describes all the variables in detail.

The coefficient of interest is β_2, which captures how partisan preference impacts lenders' mortgage approval decisions in high climate risk areas. If lenders' political preference does not impact lenders' mortgage issuance decisions, β_2 would be statistically indifferent from zero. If Republican-leaning lenders are more optimistic (pessimistic) over climate risk, we would expect β_2 to be significantly positive (negative).

My primary empirical strategy relies on two sets of high dimensional fixed effects, including county-year fixed effects, denoted by $\alpha_{c,t}$, and lender-county fixed effects, denoted by $\lambda_{b,c}$. The county-year fixed effects absorb shocks common to each county, such as changes in local economic conditions (i.e., GDP and unemployment), changes in local mortgage demands, and local real estate price fluctuations. Furthermore, I include lender-county fixed effects to control for unobserved heterogeneities between different lender-county pairs. For example, bank A's

[28]In the baseline analysis, I only include the Log(Total Applications) as the bank-year level control. In the appendix, I present the estimation results with ROA, bank size, etc. as additional control variables. Since some lenders are not banks (i.e., retail mortgage lenders), they don't have call report data. The number of observations drops by about 20% (from 24,771,654 to 19,583,258) if including other bank-year controls. For this reason, I only include Log(#Total Applications) in the main analysis.

clients may be more educated clients in an area than bank B's clients in the same region, which will impact lenders' approval rates. Finally, I double cluster standard errors by lenders and by states of mortgage applications' underlying properties.

One may wonder whether the REP Donation% variable captures lenders' views on climate risk. To address this point, I rely on the firm-level climate risk exposure data constructed by Sautner et al. (2020), which measures firm-level climate risk exposure based on the transcripts of conference calls held by companies. Table 2 presents the empirical findings, and the sample is at the lender-quarter level. There are three dependent variables: *Climate Change Exposure*, *Climate Change Risk*, and *Climate Change Sentiment*.[29] The first two measure the relative frequency of companies mentioning climate risk, and the last one measures the sentiment when companies talk about climate change. I control for heterogeneous characteristics between lenders (i.e., lenders' headquarters locations and lenders' fixed exposure to the fossil fuel and renewable industries) by including lender fixed effects. I also include time fixed effects to control for changes in the general attention to climate change. The results show that *REP Donation%* does capture lenders' beliefs in climate risk: Republican-leaning lenders are less likely to mention climate change and are more likely to express more optimistic sentiments about climate change than Democratic-leaning ones.[30]

4.2. Baseline Results: Lenders' Approval Decisions

Table 3 tests the first two hypotheses. Panel A presents the estimation results based on the second-lien mortgage application sample.[31] In Column 1, I estimate whether lenders' political preferences impact their mortgage issuance decisions. The coefficient on *REP Donation%* is statistically indifferent from zero, suggesting no evidence that *REP Donation%* affects lenders' mortgage approval decisions. In columns 2 to 4, I estimate the interaction regression as described in Equation 2. The coefficients on the interaction term, $REPDonation\% \times ClimateRisk$, are positive and significant, suggesting that Republican-leaning lenders are more likely to approve mortgage applications from high wildfire risk regions. In columns 5 to 7, I additionally

[29]See Sautner et al. (2020) for a detailed description of all three variables.

[30]See the online appendix for summary statistics of this sample.

[31]To isolate the effects of second-lien mortgages from jumbo ones, the sample of Panel A only includes second-lien mortgage applications that are also non-jumbo.

control for similar application fixed effects, which group mortgage applications that are potentially sent by one mortgage applicant to different lenders.[32] These results show that in high wildfire risk areas, even conditional on the same mortgage application, Republican-leaning lenders still have a higher approval rate than Democratic-leaning lenders. Moreover, although similar application fixed effects explain a large amount of variation (the R-squared increases from 0.192 to 0.786), my findings remain robust. Lastly, in Panel B, the findings based the jumbo applications show similar effects as Panel A, again confirming *Hypothesis 1*.

The findings in Table 3 also highlight how climate risk beliefs affect mortgage approval rates differently in high and low wildfire risk areas. Based on Column 3 of Panel A, changes in the *REP Donation%* in low-risk areas (25th percentile, High Risk = 0) do not have statistically significant effects on mortgage approval rates.[33] However, relative to low wildfire risk areas, a one-standard-deviation increase in the *REP Donation%* (0.139) in high wildfire risk areas (75th percentile, *High Risk* = 0.142) is associated with a 3.4% (= $0.139 \times 0.142 \times 1.741$) higher increase in the approval probability of mortgage applications, which is 8.1% higher relative to the average approval rate among second-lien mortgage applications (42.5%). Moreover, in areas exposed to more severe wildfire threats (i.e., those in the 90th percentile of *High Risk*), the economic magnitude will be even larger. For jumbo mortgage applications, the economic magnitude is smaller. Relative to low wildfire risk areas, a one-standard-deviation increase in the *REP Donation%* in high wildfire risk areas is associated with a 0.47% increase in the approval probability of jumbo mortgage applications. The smaller magnitude among jumbo loans might be due to the high-risk nature of second-lien mortgages.

I proceed to examine *Hypothesis 2* on whether securitization affects the lenders' incentive to consider climate risk. In Panel C of Table 3, I conduct the same mortgage approval analysis based on both first-lien and non-jumbo mortgage applications, which are mortgages that are

[32]I construct a quasi-similar application identifier by grouping mortgage applications with the same loan amounts, the same gender, the same race, the same income level, and from the same census tract. Presumably, mortgage applications with the same identifier allows me to group mortgage applications from the same mortgage applicants. Additionally, within each grouped mortgage applications, I require the first mortgage application been rejected by lenders.

[33]*High Risk* is a better variable than the other two to make inferences about economic magnitudes. *Log(WFH)* is calculated based on within-county average value of the continuous wildfire hazard (ranging from 0 to 100,000), making the variable more sensitive to large wildfire hazard values. *VHigh Risk* does not capture the land areas that are exposed to high risk.

easy to securitize. Interestingly, with a much larger sample, the coefficients on the interaction terms are neither statistically significant nor economically large. The sharp comparison between Panel A/B and Panel C indicates that lenders have little incentive to consider climate risk when evaluating applications for mortgages that are less likely to stay in lenders' portfolios, confirming *Hypothesis 2*.

4.3. Alternative Explanations

Other than the climate risk perceptions explanation, several alternative stories exist. The first one is the partisan perception of economic outlook. Depending on lenders' political alignment with the president in office, Republican-leaning and Democratic-leaning lenders can have different economic outlooks, leading to a potential difference in mortgage approval rates (Kempf and Tsoutsoura, 2021; Dagostino et al., 2020). The second alternative explanation is relative to the locations that are exposed to wildfire risks. For example, rural areas are more Republican-leaning and might also be more likely to be impacted by wildfires. Republican-leaning lenders, who are connected with Republican incumbents from the rural areas, might originate more mortgages in these areas to help these Republican politicians get re-elected (Bertrand et al., 2018; Duchin and Hackney, 2020). The third alternative explanation is about lenders' risk appetite. Republican-leaning and Democratic-leaning lenders might have exactly the same climate risk perceptions. However, Republican-leaning lenders might be generally more risk-seeking than Democratic-leaning lenders, making them more willing to invest in riskier mortgage loans from high wildfire risk areas.

The comparison between low and high wildfire risk areas suggests that the first alternative explanation does not drive my findings. If Republican and Democratic-leaning lenders have different economic outlooks, the difference in approval rates would also be observable among mortgage applications from low wildfire risk areas. In the second alternative explanation, if wildfires are more likely to happen in Republican-leaning areas (rural areas), Republican-leaning lenders might help Republican incumbents get re-elected by approving more mortgages. In Table 4, I split the sample into Republican-leaning and Democratic-leaning regions depending on how counties voted in the 2012 presidential election.[34] The findings show that the effects do not depend on whether locals are more supportive of Republicans or Democrats, suggesting that the second alternative explanation is not plausible. To examine the third alternative story, I test whether Republican-leaning lenders are more likely to approve mortgage applications from borrowers with higher loan-to-income ratios. Table 5 shows that the lenders are not more likely to originate more risky mortgages, suggesting that the risk appetite story is also not a likely explanation for the findings.

I provide two additional pieces of evidence to further support the climate risk perception explanation. First, if Republican-leaning lenders are more optimistic about wildfire risks, they are less likely to securitize mortgage loans in the secondary market after origination. To test this point, I use accepted first-lien and non-jumbo loans which are the most liquid/sellable loans in the secondary market. Table 6 presents the findings, showing that after mortgage originations, Republican-leaning lenders are indeed more likely to hold the first-lien and non-jumbo loans that are exposed to high wildfire risks in their portfolios. Second, if lenders are more concerned about climate risk, it's expected that they are more likely to deny mortgage applications for reasons related to collaterals which are endangered by climate risks (Duan and Li, 2021). Table 7 shows that among all denied loans in high wildfire risk areas, Republican-leaning lenders are less likely to deny mortgage applications for collateral-related reasons. In addition, Table 7 extends Duan and Li (2021) by highlighting how disagreement over lenders' climate risk beliefs affects their mortgage denial decisions. Thus, both Table 6 (based on accepted loans) and Table 7 (based on denied applications) support the interpretation of the climate risk perception.

4.4. Alternative Specification: Staggered Difference-in-Differences

My baseline empirical analysis is based on an interaction regression, as described in Equation 2. To estimate future climate risk, the interaction regression relies on a forward-looking wildfire hazard measurement covering the continental United States. However, one might be interested in how historical wildfire incidents affect lenders' mortgage approval decisions. Specifically, I

[34]The data on county-level presidential election results are taken from the MIT election lab. I find similar results if I classify counties as "red" or "blue" based on the 2016 presidential election.

estimate the following model using historical wildfire perimeters data from NIFC.

$$\begin{aligned} Approval_{i,b,c,t} = \alpha_{c,t} + \lambda_{b,c} + \beta_1 \times \textit{REP Donation\%}_{b,t} + \beta_2 \times \textit{REP Donation\%}_{b,t} \\ \times \textit{Wildfire Happened}_{c,t} + \theta' Controls_{i,b,c,t} + \epsilon_{i,b,c,t} \end{aligned} \tag{3}$$

The model is the same as Equation 2, except for the *Wildfire Happened* variable, which is a county-year level indicator variable on whether the county has been exposed to large-scale wildfires. More specifically, the *Wildfire Happened* variable stays at 0 before a large-scale wildfire happens and remains at 1 after it takes place in the county.

Importantly, two factors play a role in lenders' expectation of wildfire risks and thus their mortgage approval decisions: (1) the historical frequency of wildfires; (2) the severity of wildfires. First, lenders' wildfire risk expectations toward an area depend on the frequency of wildfires in the region. If wildfires occur in a county on a regular basis, it's common knowledge for both Republican-leaning and Democratic-leaning lenders that mortgages from this county are exposed to high wildfire hazard. Consequently, we won't expect a significant difference in mortgage approval rates between the optimistic and pessimistic lenders. For this reason, I restrict my analysis to counties that have experienced 3 or fewer wildfire incidents and use counties that have had more than 3 wildfire incidents as a placebo test. Second, it's straightforward to understand how wildfire severity impacts lenders' future wildfire expectations: small-scale wildfires are less likely to be noticed by lenders, thus not really affecting their mortgage approval decisions. Thus, I further restrict wildfire incidents to wildfires that consumed at least 1% of counties' land areas. The average county land area is approximately 3,050 km², making 1% of the land area about 30.5 km².

Table 8 presents the empirical findings. Panel A includes mortgage applications from counties that comply with both two requirements. As a comparison, Panel B presents estimation results for counties with more than 3 wildfire incidents. In total, there are 46 (31) counties in Panel A for second-lien (jumbo) mortgage applications. For Panel B, there are 191 (163) counties. As shown in Panel A, I find that Republican-leaning lenders are more likely than Democratic-leaning lenders to approve second-lien mortgage applications after unexpected large-scale wildfires. The effects do not survive among the jumbo mortgage applications. As for Panel B, we don't observe the effects in both second-lien sample and the jumbo sample, confirming that both Republican-leaning and Democratic-leaning lenders consider wildfire hazards if a county constantly experiences wildfires. Figure 4 plots the parallel trend of the second-lien sample in Panel A, showing that the assumption is satisfied. Given the small number of counties included in the staggered difference-in-differences sample, I continue to use the interaction regression in most of my analyses.

5 Do Optimistic Lenders Hold More Wildfire Risk?

After establishing robust evidence on how climate risk beliefs affect lenders' mortgage-approval decisions, in this section, I study whether optimistic Republican-leaning lenders are more likely to hold wildfire risks in their portfolios, leading to climate risk concentration in the financial sector. Specifically, I look at: (1) the total number of mortgage applications received by lenders in each county; (2) the total loan amount originated and the market share occupied by lenders in each county; (3) the mortgage interest rates charged by lenders; and (4) whether Republican-leaning lenders benefit from their optimistic lending policies in both the short and long term.

Figure 5 illustrates how changes in the local wildfire risk are associated with changes in the local market share of Republican-leaning lenders. The horizontal axis represents changes in *High Risk* from the beginning of the sample (2012 and 2013) to the end of the sample (2018 and 2019), and the vertical axis represents changes in the market share of Republican-leaning lenders, which is the average of lenders' *REP Donation%* weighted by lenders' market share within each county (only approved loans). Each dot represents counties with similar changes in wildfire hazards (grouped at the 0.001 scale), and the line fits across all the dots. While the fitted line has a slightly negative slope in Panel C (conforming), we observe a significantly positive slope in both Panel A (second-lien) and Panel B (jumbo), indicating that higher wildfire risks in a county are associated with a higher presence of Republican-leaning lenders in second-lien and jumbo mortgage loans. Since both second-lien and jumbo mortgage loans are likely to remain in lenders' portfolios, Figure 5 provides intuitive evidence on the increasing climate risk concentration among optimistic Republican-leaning mortgage lenders.

5.1. Number of Mortgage Applications

As detailed in *Hypothesis 3*, if borrowers' mortgage applications in high wildfire risk areas are denied by Democratic-leaning lenders, the borrowers can still shop around and file new mortgage applications with other lenders. Thus, we expect that in high wildfire risk areas, Republican-leaning lenders would receive a relatively higher number of mortgage applications than Democratic-leaning lenders. Specifically, I estimate the following empirical model:

$$\begin{aligned} Log(\#App.)_{b,c,t} = \alpha_{c,t} + \lambda_{b,c} + \beta_1 \times REP\ Donation\%_{b,t} + \beta_2 \times REP\ Donation\% \\ \times Climate\ Risk_{c,t} + \theta' Controls_{b,c,t} + \epsilon_{b,c,t} \end{aligned} \tag{4}$$

Unlike in Equation 2, the sample is at the lender-county-year level. The dependent variable, *Log(#App.)*, is the log of the number of mortgage applications received by lender b in county c in year t. *Controls* represents control variables, including the average value of Log(Loan Amount) among all mortgage applications, average Income Level, average Gender, average Race, and Log(#Tot Lender Applications). The fixed effect specification is the same as in Equation 2. Again, we are interested in the β_2 on the interaction term, $REPDonation\% \times ClimateRisk$.

Table 9 presents the estimation results. The first four columns include the sample of second-lien mortgage applications, and the last four columns include the sample of jumbo mortgage applications. I find positive and significant coefficients on all interaction terms, $REPDonation\% \times ClimateRisk$, indicating that Republican-leaning lenders receive more mortgage applications in high wildfire risk areas than Democratic-leaning lenders. In terms of economic magnitude relative to low wildfire risk areas (25th percentile *High Risk*), a one-standard-deviation increase in the REP Donation% in high wildfire risk areas (75th percentile of *High Risk*) is associated with a 5.72% (2.15%) higher increase in the number of second-lien (jumbo) mortgage applications. Therefore, the findings confirm that Republican-leaning lenders benefit from their higher tolerance of climate risk by receiving a greater number of mortgage applications in high wildfire risk areas.[35]

[35] Given that the number of applications is a count variable, Table A.8 presents the alternative Poisson estimation (Cohn et al., 2021).

5.2. The Holding of Wildfire Exposed Mortgages

Given higher approval rates and the higher number of mortgage applications, it's obvious that Republican-leaning lenders originate more mortgages in high wildfire risk areas. In Table 10, I estimate whether Republican-leaning lenders originate a greater number of mortgage loans in high wildfire risk areas.[36] The sample is at the lender-county-year level.

The findings confirm this intuition. The magnitude is also economically sizable. Relative to low fire risk areas (25th percentile), a one-standard-deviation increase in *REP Donation%* in high fire risk areas (75th percentile) is associated with a 9.3% (2.9%) increase in the total number of second-lien (jumbo) mortgage loans. The average value for the total number of originated second-lien (jumbo) at lender-county-year level is $841,313$(15,984,184). Therefore, at the bank-county-year level, the magnitude is approximately \$78,040 (\$466,274) for second-lien (jumbo) loans. After counting the number of counties with *High Risk* that is greater than the 75th percentile, the effects at the lender-year level are about \$48 million (\$130 million) for second-lien (jumbo) loans.[37] Considering that *High Risk* at the 75th percentile represents the minimal value of *High Risk* among the top quartile counties, the \$48 million (\$130 million) represents the lower bound of the estimated effects.

5.3. Mortgage Interest Rate Charged

The findings have documented the quantity effects: optimistic Republican-leaning lenders are more likely to invest in mortgage loans exposed to high wildfire risks. I next examine the price effects: whether Republican-leaning lenders and Democratic-leaning lenders charge different mortgage interest rates in high wildfire risk areas. However, the interest rate effects are subject to important data limitations. The HMDA data only started including the interest rate variable in 2018.[38] Although the single-family loan performance data from Fannie Mae and Freddie Mac provide mortgage interest rate information, they only cover conforming loans. As shown earlier,

[36] I conduct similar tests based on the number of approved mortgage applications, as well as the market share of each lender. The findings are similar.

[37] For the second-lien sample, there are on average 610 counties that are exposed to high wildfire risks each year. The number is 280 for the jumbo mortgage sample.

[38] Almost 95% of approved mortgage applications from before 2018 in the HMDA data don't have interest rate information (the rate spread variable).

Republican-leaning and Democratic-leaning lenders are indifferent in approving conforming mortgage applications and thus unlikely to charge different interest rates for conforming loans.

Table 11 estimates the interest rate effects based on the single-family loan performance data. The samples are at mortgage loan level. The table relies on the single-family loan performance data. The most granular geographic information in the single-family loan performance data is at the 3-digit zip code level.[39] Thus, I re-calculate the wildfire risk at the 3-digit zip code level. As expected, I find that Republican and Democratic-leaning lenders are statistically indifferent in charging mortgage interest rates for mortgages from high wildfire risk areas.

5.4. Optimal Lending Policies

One important question left unanswered is whether Republican-leaning lenders benefit from their optimistic lending policies in high wildfire risk areas both in the short term and in the long term. Answering this question has similar data limitations as the interest rate effects do. In this paper, I only observe the performance of conforming loans and don't observe the performance of second-lien or jumbo mortgages. Following the same reasoning of mortgage securitization, it's unlikely that differences would be observed in the mortgage delinquency rate of conforming loans at the mortgage level, and therefore at the mortgage-lender level. More importantly, as an econometrician, I don't know the true parameter on the likelihood of future wildfire incidents, making it almost impossible to conduct an ex-ante cost benefits analysis for lenders. Given these limitations, I make attempts to address this question using the limited single-family loan performance data, as well some economic reasoning that supports my conclusion.

In Table 12, I use the single-family loan performance data to estimate whether mortgages originated by Republican-leaning and Democratic-leaning lenders have different delinquency rates after exposure to wildfire incidents. *REP Donation%* is estimated at the mortgage origination, and *Wildfire Impacted Area%* is the fraction of land areas that are exposed to wildfires in the 3-digit zip code in a year. The results in Column 1 confirm Issler et al. (2020), who find that mortgage delinquency rates increase significantly after wildfire incidents. As expected, I don't

[39]There are approximately 900 different 3-digit zip codes in the United States.

observe a significant difference in mortgage delinquency rates between Republican-leaning and Democratic-leaning lenders. In Column 2, the coefficient on the interaction term is significant at 10%, and the effect is economically very small. For the largest wildfire incidents,(those in the 99th percentile by *Wildfire Impacted Area%*), a one-standard-deviation increase in *REP Donation%* is associated with only a 2.3 basis point increase in mortgage default probability. Therefore, the results suggest that we cannot conduct a cost-benefit analysis using conforming loan data.

However, based on existing evidence, one can infer that optimistic Republican-leaning lenders experience losses around large fire incidents. We know: (1) mortgage delinquency rates increase after large-scale wildfires, as seen in Column 1 of Table 12 and Issler et al. (2020); and (2) optimistic Republican-leaning lenders hold more second-lien and jumbo mortgages in high wildfire risk areas (Table 10). Therefore, it's obvious that Republican-leaning lenders will experience a higher number of mortgage defaults after wildfires, thus bearing losses from mortgage delinquencies. If both the interest rates and the loan performance of second-lien and jumbo mortgages are available, it's possible to make an ex-post analysis on whether Republican-leaning lenders on average experience losses after wildfires. Again, without knowing the true risk parameter of wildfires, I won't be able to make an inference on the ex-ante optimal policy. Moreover, the true parameter of wildfire probability is also evolving over time depending on how global warming proceeds, making it even harder to estimate the long-term optimal lending policy.

6 Further Analysis

In this section, I study other types of climate risk, examine real effects, and also provide a battery of robustness tests.

6.1. Other Types of Climate Risk

The effects of climate change take various forms. Mortgage lenders can have different priorities for different types of climate risk. In this section, I study the relative importance of different climate risks, including wildfires, sea-level rise, and floods. The findings are generally consistent with *Hypothesis 4*, suggesting that wildfire risk plays a more important role in mortgage lenders' mortgage issuance decisions than does sea-level rise or flooding.

Table 13 presents the empirical results. As defined in Section 3.4 and Table A.1, *SLR 5 Feet* estimates the fraction of land that will be underwater if the sea level rises by 5 feet, and *High Risk (Flood)* measure the fraction of county areas that are exposed to high flood risk. The findings suggest that lenders consider the sea-level rise and flood risk for second-lien mortgage applications (Column 1 and Column 2) but not for jumbo applications (Column 5 and Column 6). The difference might be due to the high-risk nature of second-lien mortgages, making lenders more cautious when approving such mortgages. The other columns compare wildfire risk with the other two types of climate risks. Due to the potential collinearity between *High Risk (Flood)* and *SLR 5 Feet*, I separately estimate the effects. The findings indeed show that wildfire risk represents a more severe threat than the other two risks. As described in *Hypothesis 4*, the reason is likely because of insurance coverage and the more immediate threat of wildfires.

6.2. Real Effects

The last question is whether the increasing presence of Republican-leaning lenders has real effects on the local economy. To examine this issue, I rely on several data sources, including real estate price data from Zillow, local GDP, FDIC bank deposit branch information, and employment from BEA. To capture the presence of Republican-leaning lenders in local areas, I calculate the weighted average of *REP Donation%* (weighted by the number of branches in the region). Table 14 presents the estimation results on real effects. The findings suggest no real effects in high-risk areas.

6.3. Robustness

In this subsection, I present robustness tests. The results are generally consistent and robust. First, one may be concerned about the large sample size and corresponding large sample bias. To alleviate this concern, I collapse the sample from the mortgage application level to the lender-county-year level. For each lender-county-year pair, I construct a new dependent variable on the percentage of applications that are ultimately approved. To avoid extreme values, such as 0 or 1, I only include lender-county-year pairs that have at least 3 mortgage applications. Table A.5 presents the findings based on the lender-county-year level sample. The results are robust to the lender-county-year level sample. Second, Table A.6 provides estimation results based on *REP Donation%* with 3 and 5 years. The findings remain the same. Third, large mortgage lenders receive many more applications. It will be informative to see if the findings hold after removing the largest lenders. Table A.7 provides the estimation results after removing the top 10 largest lenders. While the results become weaker for the jumbo mortgage applications, they remain strong for the second-lien mortgage applications. Finally, I provide estimation results with census tract-year and lender-census tract fixed effects in Appendix Table 10, and the findings are similar.

7 Conclusion

Using the mortgage market as a laboratory, I document that disagreement over climate risk beliefs leads to self-sorting among institutional investors in holding climate risk. Building on the literature and survey evidence, I use mortgage lenders' political preferences to capture their perceptions on climate change. I find that Republican-leaning lenders are more likely to approve mortgage applications that are exposed to high wildfire risks. Importantly, the effects only exist among hard-to-securitize second-lien and jumbo mortgages, highlighting how securitization reduces lenders' incentive to consider climate risk. I also show that Republican-leaning lenders also originate more second-lien and jumbo loans in high wildfire areas and thus hold more wildfire risks in their portfolios.

The findings have implications on the financial stability and also for future research. As many have argued, climate change is generally recognized as one of the defining challenges of our time. Over the last several years, we have also witnessed an acceleration of weather-related adverse events, such as wildfires, droughts, floods, etc. Although we don't know the exact impacts of climate change, there is a non-trivial probability that climate change will severely impact the economy in a systematic way. From the perceptive of financial stability, it's better to have a large scale of risk-sharing across financial institutions. However, my findings show that without intervention, it's more likely to have risk concentration instead of risk-sharing, which creates policy implications around disclosing climate risk exposure, stress testing, etc.

Finally, while my paper uses the mortgage market as a setting to study how disparate climate risk beliefs lead to climate risk concentration, the general mechanism can also take place in other markets and different settings, which can be interesting for future research.

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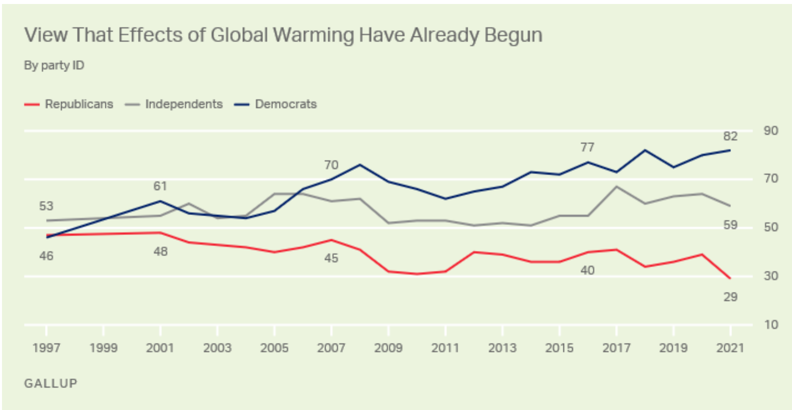
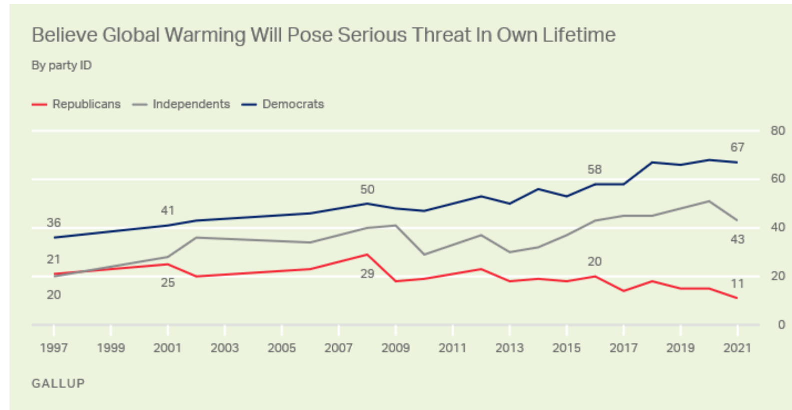
Figure 1: Survey Evidence on the Partisan Divide over Climate Change Beliefs

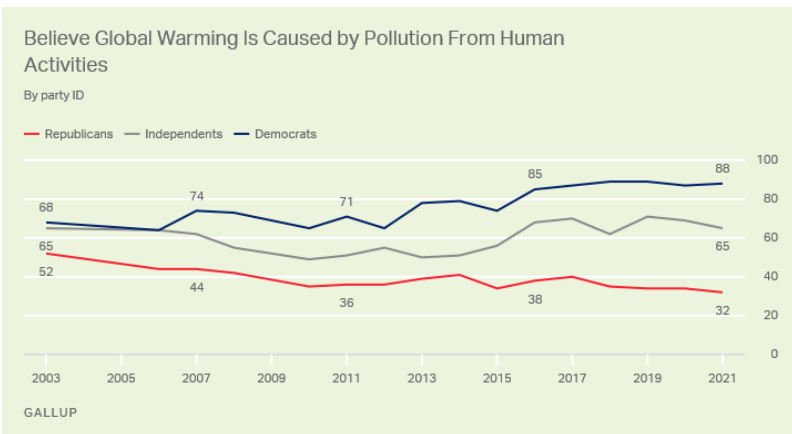
This Figure presents survey evidence on the partisan divide over climate change beliefs from both Gallup (Panel A to Panel C) and Pew Research Center (Panel D). For Panel A to Panel C, see "Global Warming Attitudes Frozen Since 2016", *Gallup*, April 5, 2021. For Panel D, see "U.S. concern about climate change is rising, but mainly among Democrats", *Pew Research Center*, April 16, 2020.



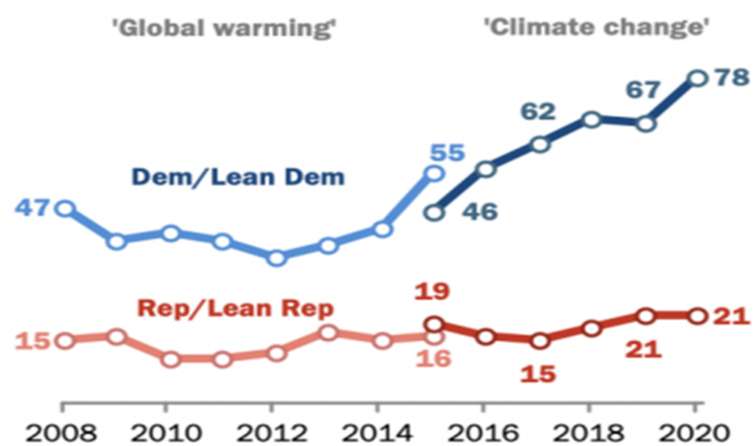
(a) Global-Warming have already begun (Gallup)



(b) Global-Warming will pose serious threat in own lifetime (Gallup)



(c) Global-Warming is caused by human activities (Gallup)



(d) Global-Warming should be a top priority for the government (Pew)

Figure 2: Temperature Anomaly and Wildfires

The data on wildfire acres are obtained from the National Interagency Fire Center (NIFC), and the data on global temperature anomaly are from the National Oceanic and Atmospheric Administration. Temperature anomaly is measured relative to the average temperature in the 20th century. NIFC doesn't track wildfire information before 1983.

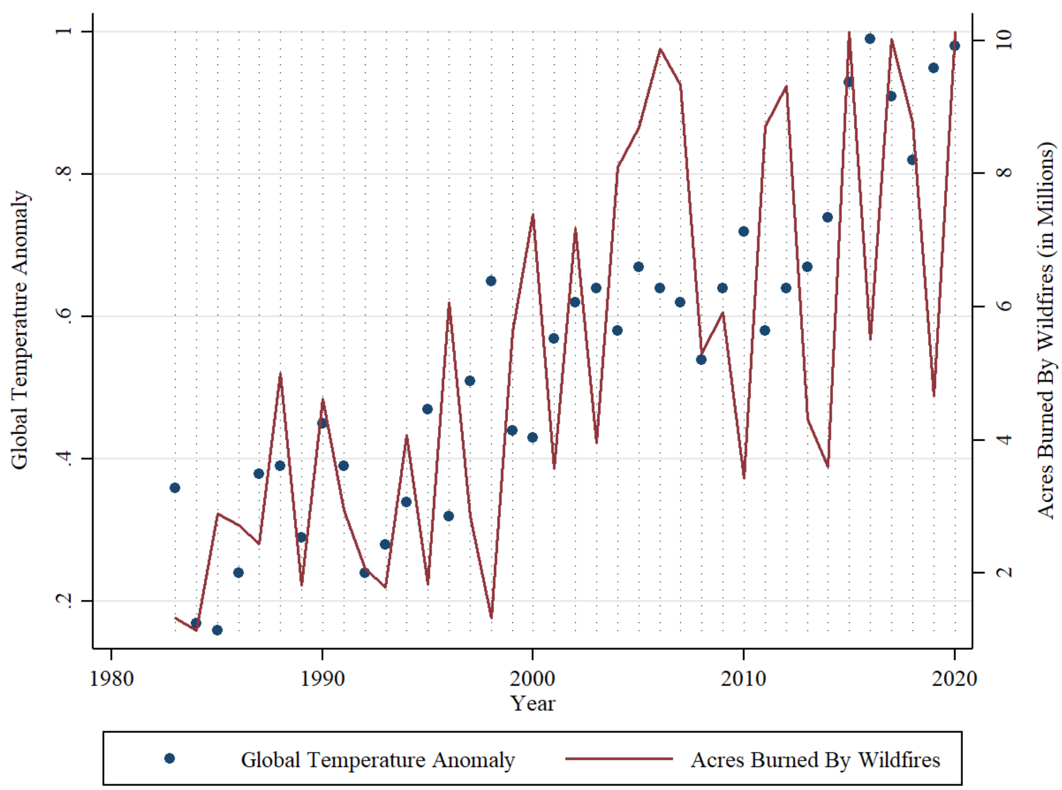


Figure 3: The 2018 Wildfire Hazard Potential map

The figure presents the 2018 version of Wildfire Hazard Potential map developed by USDA Forest Service. The goal of the map is *"to depict the relative potential for wildfire that would be difficult for suppression resources to contain"*. Areas are classified into five classes of wildfire risks, including very low risk (green), low risk (light green), moderate risk (yellow), high risk (orange), and very high risk (red). Alaska and Hawaii are not included in the map. The full description of the Wildfire Hazard Potential map is available at the USDA Forest Service website.

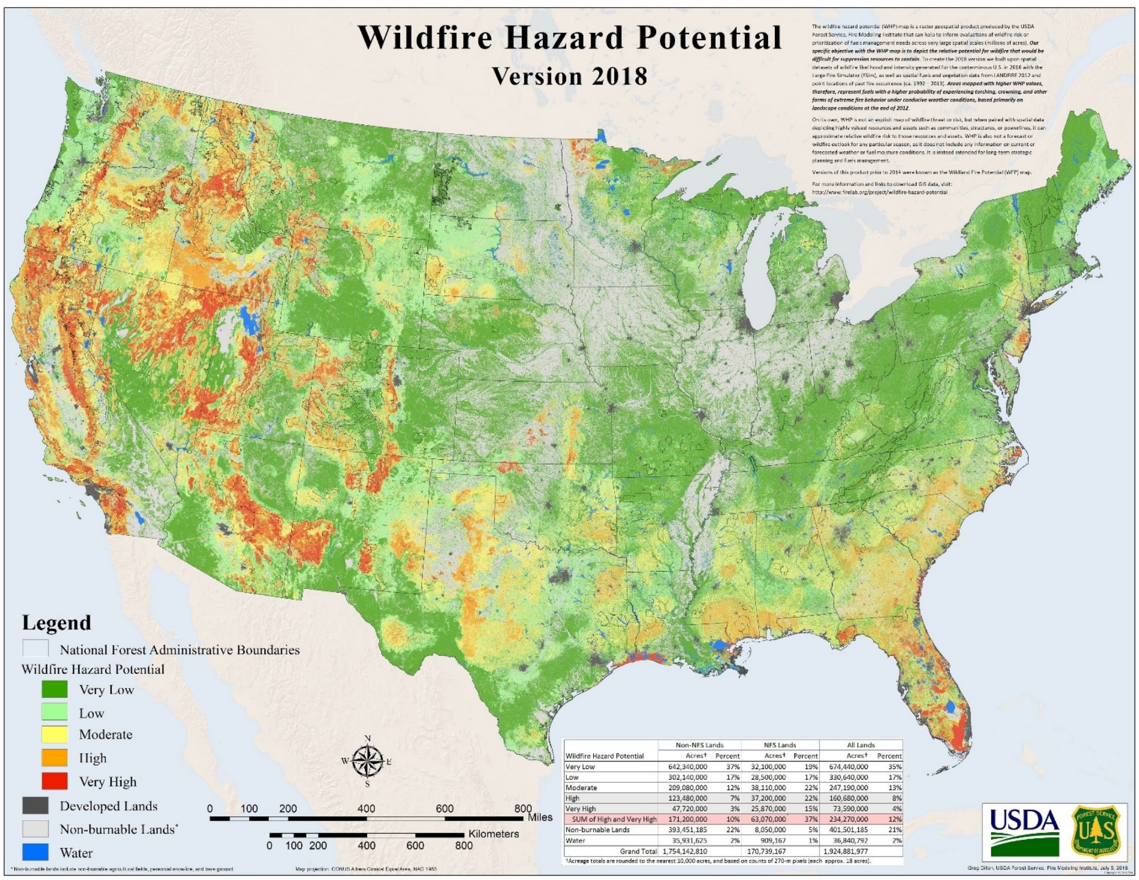


Figure 4: Parallel Trends around Wildfire Incidents

This figure plots the parallel trends around large fire incidents. The figure corresponds to column 1 of the Table 8. The baseline is years before *t-3*.

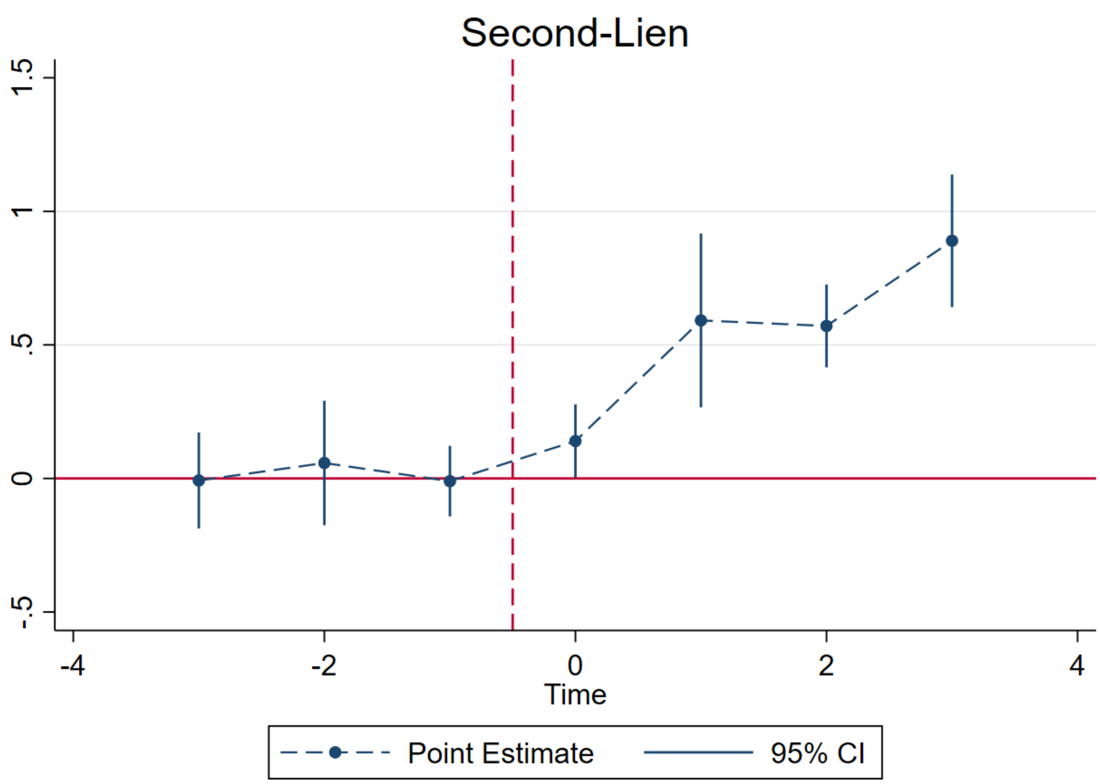


Figure 5: Local Wildfire Hazard and Republican-Lean Lenders' Market Share

The figure provides non-parametric analysis on the effects of wildfire hazard and Republican-lenders' market share. The horizontal axis represents county-level changes of wildfire risks between the first two years (2012-2013) and the last two years (2018-2019) in the sample. Similarly, the vertical axis represents the changes in the market share of Republican-leaning lenders, which is the *Rep Donation%* weighted by lenders' market share within each county.

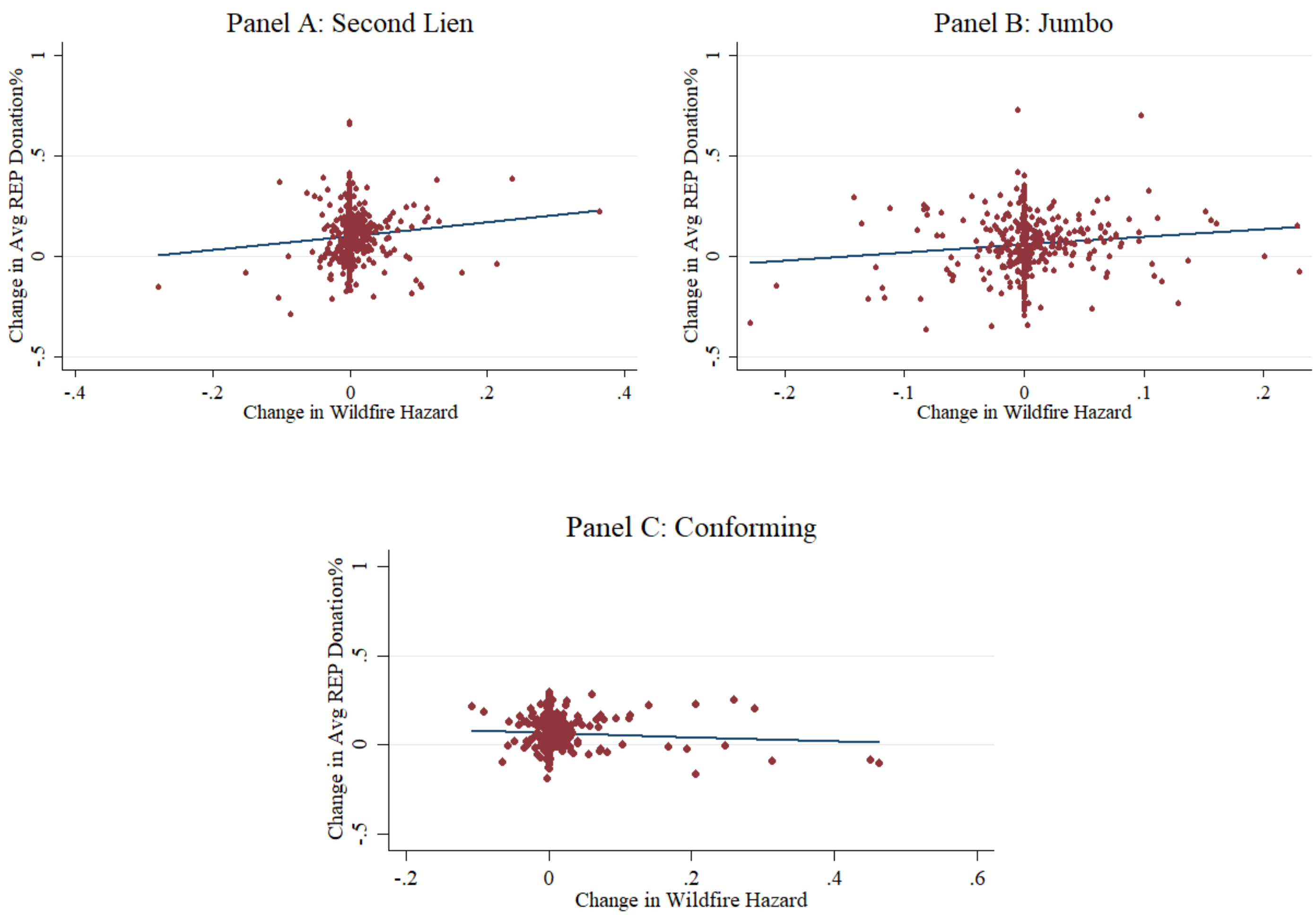


Table 1: Summary Statistics - Mortgage Application Sample

This table presents summary statistics of the mortgage approval sample. All samples are at the mortgage application level. Panel A represents the sample on second-lien mortgage applications, Panel B represents the sample on jumbo mortgage applications, and Panel C represents the sample on conforming mortgage applications.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second-Lien	N	mean	p25	p50	p75	sd
Approval	2,464,455	0.425	0.000	0.000	1.000	0.494
REP Donation%	2,464,455	0.702	0.596	0.659	0.830	0.139
Log(WFH)	2,464,455	3.894	2.213	4.130	5.407	2.238
High Risk	2,464,455	0.095	0.000	0.003	0.142	0.154
VHigh Risk	2,464,455	0.029	0.000	0.000	0.002	0.084
Income Level	2,464,455	2.221	2.000	2.000	3.000	0.648
Male	2,464,455	0.573	0.000	1.000	1.000	0.495
White	2,464,455	0.703	0.000	1.000	1.000	0.457
Log(Loan Amount)	2,464,455	10.062	9.210	10.127	10.915	1.208
Log(#Tot Lender Applications)	2,464,455	11.249	10.467	11.169	12.891	1.703

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Jumbo	N	mean	p25	p50	p75	sd
Approval	1,786,382	0.811	1.000	1.000	1.000	0.392
REP Donation%	1,786,382	0.632	0.586	0.624	0.659	0.110
Log(WFH)	1,786,382	5.025	3.156	5.164	7.087	2.386
High Risk	1,786,382	0.171	0.000	0.084	0.314	0.183
VHigh Risk	1,786,382	0.072	0.000	0.000	0.134	0.102
Income Level	1,786,382	2.970	3.000	3.000	3.000	0.198
Male	1,786,382	0.751	1.000	1.000	1.000	0.432
White	1,786,382	0.688	0.000	1.000	1.000	0.463
Log(Loan Amount)	1,786,382	13.617	13.318	13.534	13.820	0.430
Log(#Tot Lender Applications)	1,786,382	11.775	10.927	12.162	12.896	1.529

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: Conforming	N	mean	p25	p50	p75	sd
Approval	19,288,215	0.755	1.000	1.000	1.000	0.430
REP Donation%	19,288,215	0.648	0.585	0.636	0.705	0.129
Log(WFH)	19,288,215	4.120	2.295	4.296	5.767	2.323
High Risk	19,288,215	0.107	0.000	0.009	0.171	0.158
VHigh Risk	19,288,215	0.037	0.000	0.000	0.021	0.083
Income Level	19,288,215	2.301	2.000	2.000	3.000	0.606
Male	19,288,215	0.614	0.000	1.000	1.000	0.487
White	19,288,215	0.731	0.000	1.000	1.000	0.443
Log(Loan Amount)	19,288,215	11.978	11.562	12.014	12.476	0.685
Log(#Tot Lender Applications)	19,288,215	11.922	11.053	12.292	12.879	1.416

Table 2: Firm-Level Climate Risk Exposure and *REP Donation%*

The regressions are estimated at the lender-quarter level. *Climate Change Exposure* measures the relative frequency of managers mentioning climate change on conference calls. *Climate Change Risk* measures the relative frequency of managers mentioning climate change together with words like risk. *Climate Change Sentiment* captures the sentiments when managers mention climate change. Standard errors double clustered by quarter and lender are reported in parentheses below the coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	(1) Climate Change Risk	(2) Climate Change Exposure	(3) Climate Change Sentiment
REP Donation%	-0.007**	-0.083**	0.021*
	(0.003)	(0.034)	(0.012)
Log(#Tot Lender Applications)	-0.000	-0.001**	-0.000
	(0.000)	(0.000)	(0.000)
Observations	1,549	1,549	1,549
R-squared	0.128	0.471	0.182
Quarter FE	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes

Table 3: Mortgage Approval Rates

This table presents the estimations results of Equation 2. All samples are at the mortgage application level. The dependent variable, Approval, is an indicator variable set to one if the mortgage application is approved. Panel A includes *Second-Lien* mortgage applications. Panel B includes *Jumbo* mortgage applications. Panel C includes *Conforming* mortgage applications. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. For the full specification including control variables, see appendix Table A.4. *** p < 0.01, ** p < 0.05, * p < 0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Second-Lien	Approval	Approval	Approval	Approval	Approval	Approval	Approval
REP Donation%	0.331	-0.161	0.249	0.305	-0.293	0.211	0.298
	(0.268)	(0.243)	(0.248)	(0.261)	(0.196)	(0.260)	(0.277)
REP Donation% × Log(WFH)		0.171***			0.232***		
		(0.049)			(0.045)		
REP Donation% × High Risk			1.741***			2.634***	
			(0.384)			(0.401)	
REP Donation% × VHigh Risk				1.933***			3.283***
				(0.175)			(0.335)
Observations	2,464,455	2,464,455	2,464,455	2,464,455	2,464,455	2,464,455	2,464,455
R-squared	0.191	0.192	0.192	0.192	0.894	0.894	0.894
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Similar Application FE	No	No	No	No	Yes	Yes	Yes

Table 3 (Continued)

Panel B: Jumbo	(1) Approval	(2) Approval	(3) Approval	(4) Approval	(5) Approval	(6) Approval	(7) Approval
REP Donation%	0.067	-0.024	0.044	0.042	0.034	0.108	0.045
	(0.126)	(0.135)	(0.148)	(0.130)	(0.166)	(0.160)	(0.135)
REP Donation% × Log(WFH)		0.018***			0.022***		
		(0.001)			(0.006)		
REP Donation% × High Risk			0.136***			0.241**	
			(0.043)			(0.106)	
REP Donation% × VHigh Risk				0.333***			1.100***
				(0.021)			(0.152)
Observations	1,786,382	1,786,382	1,786,382	1,786,382	1,786,382	1,786,382	1,786,382
R-squared	0.118	0.118	0.118	0.118	0.918	0.918	0.918
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Similar Application FE	No	No	No	No	Yes	Yes	Yes

Panel C: Conforming	(1) Approval	(2) Approval	(3) Approval	(4) Approval	(5) Approval	(6) Approval	(7) Approval
REP Donation%	-0.132	-0.102	-0.131	-0.129	-0.103	-0.084	-0.070
	(0.151)	(0.133)	(0.150)	(0.151)	(0.107)	(0.107)	(0.107)
REP Donation% × Log(WFH)		-0.008			0.011		
		(0.006)			(0.012)		
REP Donation% × High Risk			-0.012			0.228**	
			(0.086)			(0.099)	
REP Donation% × VHigh Risk				-0.093			0.178
				(0.291)			(0.240)
Observations	19,288,215	19,288,215	19,288,215	19,288,215	19,288,215	19,288,215	19,288,215
R-squared	0.091	0.091	0.091	0.091	0.925	0.925	0.925
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Similar Application FE	No	No	No	No	Yes	Yes	Yes

Table 4: Mortgage Approval Rates in "Blue" and "Red" Areas

This table presents estimation results by splitting the sample into "blue" and "red" counties. All estimations are at the mortgage application level. The dependent variable, Approval, is an indicator variable set to one if the mortgage application is approved. Columns 1 to 3 represent mortgage applications that are second-lien and non-jumbo. Columns 4 to 6 represent mortgage applications that are jumbo and first-lien. Panel A includes "red" counties that voted Republican in the 2012 presidential election. Panel B includes "blue" counties that voted Democratic in the 2012 presidential election. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Second-Lien			Jumbo		
Panel A: Blue Counties	(1) Approval	(2) Approval	(3) Approval	(4) Approval	(5) Approval	(6) Approval
REP Donation%	-0.072	0.293	0.329	-0.034	0.043	0.037
	(0.271)	(0.261)	(0.269)	(0.145)	(0.159)	(0.137)
REP Donation% × Log(WFH)	0.154**			0.020***		
	(0.057)			(0.001)		
REP Donation% × High Risk		1.375***			0.111**	
		(0.427)			(0.048)	
REP Donation% × VHigh Risk			1.237***			0.322***
			(0.165)			(0.030)
Log(Loan Amount)	0.007	0.007	0.007	-0.041***	-0.041***	-0.041***
	(0.011)	(0.010)	(0.011)	(0.006)	(0.006)	(0.006)
Income Level	0.172***	0.172***	0.172***	0.400***	0.400***	0.400***
	(0.008)	(0.008)	(0.008)	(0.018)	(0.018)	(0.020)
Male	0.004	0.004	0.004	0.001	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
White	0.100***	0.100***	0.100***	0.009**	0.009**	0.009**
	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
Log(#Tot Lender Applications)	0.007	0.007	0.008	-0.026	-0.026	-0.026
	(0.006)	(0.006)	(0.007)	(0.017)	(0.017)	(0.017)
Observations	1,367,279	1,367,279	1,367,279	1,371,703	1,371,703	1,371,703
R-squared	0.188	0.188	0.187	0.100	0.100	0.100
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4 (Continued)

Panel B: Red Counties	Second-Lien (1) Approval	Second-Lien (2) Approval	Second-Lien (3) Approval	Jumbo (4) Approval	Jumbo (5) Approval	Jumbo (6) Approval
REP Donation%	-0.354	0.157	0.240	0.025	0.043	0.057
	(0.239)	(0.237)	(0.250)	(0.102)	(0.118)	(0.112)
REP Donation% × Log(WFH)	0.209***			0.011**		
	(0.051)			(0.004)		
REP Donation% × High Risk		2.379***			0.254***	
		(0.408)			(0.042)	
REP Donation% × VHigh Risk			5.040***			0.461***
			(0.608)			(0.044)
Log(Loan Amount)	0.010	0.010	0.010	-0.062***	-0.062***	-0.062***
	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)	(0.006)
Income Level	0.158***	0.158***	0.158***	0.381***	0.381***	0.381***
	(0.009)	(0.009)	(0.009)	(0.019)	(0.020)	(0.018)
Male	0.016***	0.016***	0.016***	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
White	0.092***	0.092***	0.092***	0.015***	0.015***	0.015***
	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)
Log(#Tot Lender Applications)	0.008	0.009	0.009	-0.025*	-0.025*	-0.025*
	(0.006)	(0.006)	(0.006)	(0.015)	(0.015)	(0.015)
Observations	1,097,176	1,097,176	1,097,176	414,679	414,679	414,679
R-squared	0.196	0.195	0.195	0.166	0.166	0.166
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: General Risk Tolerance

This table tests whether Republican-leaning and Democratic-leaning lenders have significant difference in risk tolerance. The sample is at the mortgage application level. Loan to Income represents the ratio between loan amounts and applicant income. The other variables are the same as the previous tables. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Second-Lien		Jumbo	
	(1)	(2)	(3)	(4)
	Approval	Approval	Approval	Approval
REP Donation%	0.313	0.357	0.086	0.067
	(0.251)	(0.262)	(0.123)	(0.119)
Loan to Income	-0.051**	-0.048*	-0.068***	-0.060***
	(0.024)	(0.027)	(0.006)	(0.007)
REP Donation% × Loan to Income	-0.051	-0.035	0.000	0.007
	(0.035)	(0.038)	(0.010)	(0.010)
Log(Loan Amount)		0.042***		-0.026***
		(0.012)		(0.005)
Income Level		0.120***		0.207***
		(0.009)		(0.017)
Male	0.031***	0.009***	-0.002	-0.002
	(0.003)	(0.003)	(0.004)	(0.004)
White	0.109***	0.096***	0.009*	0.009**
	(0.008)	(0.006)	(0.004)	(0.004)
Log(#Tot Lender Applications)	0.010	0.009	-0.025	-0.025
	(0.009)	(0.007)	(0.017)	(0.016)
Observations	2,464,455	2,464,455	1,786,382	1,786,382
R-squared	0.168	0.198	0.141	0.150
County-Year FE	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes

Table 6: Securitization of Mortgage Loans After Origination

This table presents the estimation results of how lenders securitize their mortgages after origination. The sample is at the mortgage level and only includes originated mortgages that are *conforming* loans (the most liquid mortgages). The dependent variable, Hold, is an indicator variable that equals one if lenders do not sell the mortgage in the secondary market. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. *** p < 0.01, ** p < 0.05, * p < 0.1

	(1) Hold	(2) Hold	(3) Hold	(4) Hold
REP Donation%	0.072	-0.010	0.045	0.054
	(0.146)	(0.124)	(0.140)	(0.143)
REP Donation% × Log(WFH)		0.021**		
		(0.009)		
REP Donation% × High Risk			0.281**	
			(0.108)	
REP Donation% × VHigh Risk				0.532**
				(0.239)
Log(Loan Amount)	-0.053**	-0.053**	-0.053**	-0.053**
	(0.026)	(0.026)	(0.026)	(0.026)
Income Level	0.029***	0.029***	0.029***	0.029***
	(0.008)	(0.009)	(0.008)	(0.008)
Male	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
White	-0.009**	-0.009**	-0.009**	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Log(#Tot Lender Applications)	-0.073**	-0.073*	-0.073*	-0.073*
	(0.036)	(0.036)	(0.036)	(0.036)
Observations	14,559,710	14,559,710	14,559,710	14,559,710
R-squared	0.231	0.231	0.231	0.231
County-Year FE	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes

Table 7: Reasons for Mortgage Applications Been Denied

This table presents the estimation results for the reasons for a mortgage denial. The sample is at the mortgage application level and only includes denied mortgage applications. The dependent variable, Collateral, is an indicator variable that equals one if lenders list collateral as the reason for rejecting the mortgage applications. Columns 1 to 4 include the denied mortgages that are second-lien and non-jumbo. Columns 5 to 8 include the denied mortgages that are jumbo and first lien. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Second-Lien				Jumbo			
	(1) Collateral	(2) Collateral	(3) Collateral	(4) Collateral	(5) Collateral	(6) Collateral	(7) Collateral	(8) Collateral
REP Donation%	0.177	0.548*	0.254	0.210	0.130	0.177	0.154	0.127
	(0.145)	(0.268)	(0.154)	(0.146)	(0.126)	(0.127)	(0.141)	(0.135)
REP Donation% × Log(WFH)		-0.122*				-0.009***		
		(0.069)				(0.002)		
REP Donation% × High Risk			-1.196**				-0.138***	
			(0.458)				(0.037)	
REP Donation% × VHigh Risk				-1.576***				0.037
				(0.186)				(0.113)
Log(Loan Amount)	0.030**	0.030**	0.030**	0.030**	0.025**	0.025**	0.025**	0.025**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.010)	(0.010)	(0.010)	(0.010)
Income Level	0.055***	0.055***	0.055***	0.055***	0.121***	0.121***	0.121***	0.121***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Male	0.010**	0.010**	0.010**	0.010**	-0.004*	-0.004*	-0.004*	-0.004*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
White	0.012**	0.012**	0.012**	0.012**	0.021***	0.021***	0.021***	0.021***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)
Log(#Tot Lender Applications)	-0.007	-0.005	-0.006	-0.006	-0.024*	-0.024*	-0.024*	-0.024*
	(0.006)	(0.005)	(0.006)	(0.006)	(0.013)	(0.013)	(0.013)	(0.013)
Observations	1,325,066	1,325,066	1,325,066	1,325,066	338,368	338,368	338,368	338,368
R-squared	0.220	0.221	0.221	0.221	0.167	0.167	0.167	0.167
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Staggered Difference-in-Differences Tests

The table presents the staggered Difference-in-Differences tests around wildfires incidents. The sample is at the mortgage-application level. *Wildfire Happened* is an indicator variable of whether a county has been exposed to wildfires that consume over 1% of the county's area. The first 2 columns represent counties with fewer than or equal to 3 historical wildfire incidents, and the last 2 columns represent the counties with more than 3 historical wildfires. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property county and lender are reported in parentheses below the coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Counties (<=3 Fires)		Counties (>3 Fires)	
	(1) Approval (2nd-Lien)	(2) Approval (Jumbo)	(3) Approval (2nd-Lien)	(4) Approval (Jumbo)
REP Donation%	0.655**	0.234*	1.022***	0.180
	(0.289)	(0.123)	(0.214)	(0.185)
REP Donation% × Wildfire Happened	0.504***	-0.007	0.241	-0.160
	(0.027)	(0.047)	(0.145)	(0.110)
Log(Loan Amount)	-0.009	-0.046***	-0.021***	-0.052***
	(0.007)	(0.012)	(0.007)	(0.007)
Income Level	0.156***	0.373***	0.187***	0.407***
	(0.007)	(0.023)	(0.015)	(0.026)
Male	0.007**	-0.002	0.009*	0.004
	(0.003)	(0.011)	(0.005)	(0.004)
White	0.089***	0.021***	0.081***	0.009*
	(0.010)	(0.005)	(0.012)	(0.005)
Log(#Tot Lender Applications)	-0.002	-0.001	-0.037***	-0.030*
	(0.004)	(0.014)	(0.011)	(0.018)
Observations	38,999	24,529	148,885	364,594
R-squared	0.144	0.143	0.134	0.088
County-Year FE	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes

Table 9: Number of Received Mortgage Applications

This table presents the estimation results for the number of mortgage applications received by lenders. The sample is at the lender-county-year level. The dependent variable, *Log(#App.)*, is the log of the number of mortgage applications received by lenders in the county and year. Columns 1 to 4 include the number of mortgage applications that are jumbo and first lien. Columns 5 to 8 include the number of mortgages applications that are non-jumbo and second lien. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. For robustness, I conduct the same tests with Poisson estimation in the appendix Table A.8. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Second-Lien				Jumbo			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(#App.)	Log(#App.)	Log(#App.)	Log(#App.)	Log(#App.)	Log(#App.)	Log(#App.)	Log(#App.)
REP Donation%	0.074	-1.548	-0.154	0.035	0.058	-0.475	-0.033	0.008
	(0.676)	(1.028)	(0.685)	(0.672)	(0.334)	(0.349)	(0.336)	(0.338)
REP Donation% × Log(WFH)		0.587***				0.137***		
		(0.209)				(0.046)		
REP Donation% × High Risk			5.618**				0.932*	
			(2.125)				(0.468)	
REP Donation% × VHigh Risk				6.081**				1.571**
				(2.356)				(0.634)
Avg Loan Amount	0.054	0.056	0.055	0.054	0.054**	0.054**	0.054**	0.054**
	(0.062)	(0.062)	(0.062)	(0.062)	(0.022)	(0.022)	(0.022)	(0.022)
Avg Income Level	-0.102***	-0.101***	-0.101***	-0.101***	0.057**	0.056**	0.056**	0.056**
	(0.028)	(0.027)	(0.027)	(0.028)	(0.023)	(0.023)	(0.023)	(0.023)
Avg Male	-0.007	-0.007	-0.007	-0.008	-0.005	-0.004	-0.004	-0.004
	(0.022)	(0.022)	(0.021)	(0.022)	(0.015)	(0.015)	(0.015)	(0.015)
Avg White	-0.018	-0.015	-0.016	-0.017	-0.021*	-0.020	-0.021*	-0.021*
	(0.043)	(0.042)	(0.043)	(0.043)	(0.012)	(0.012)	(0.012)	(0.012)
Log(#Tot Lender Applications)	0.121	0.119	0.121	0.121	0.223***	0.222***	0.222***	0.222***
	(0.112)	(0.111)	(0.111)	(0.112)	(0.068)	(0.068)	(0.068)	(0.068)
Observations	92,340	92,340	92,340	92,340	96,325	96,325	96,325	96,325
R-squared	0.903	0.904	0.903	0.903	0.906	0.906	0.906	0.906
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Total Amount of Approved Mortgage Loans

This table presents the estimation results on the county-level amount originated by lenders. The sample is at the lender-county-year level. The dependent variable, *Log(Tot Amt)*, is the log of the total mortgage amounts originated by lenders at county level. Columns 1 to 4 represent the second-lien and non-jumbo. Columns 5 to 8 represent the jumbo and first-lien. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. *** p < 0.01, ** p < 0.05, * p < 0.1

	Second-Lien				Jumbo			
	(1) Log(Tot Amt)	(2) Log(Tot Amt)	(3) Log(Tot Amt)	(4) Log(Tot Amt)	(5) Log(Tot Amt)	(6) Log(Tot Amt)	(7) Log(Tot Amt)	(8) Log(Tot Amt)
REP Donation%	0.590	-1.628	0.275	0.533	0.163	-0.442	0.043	0.112
	(0.910)	(1.297)	(0.897)	(0.914)	(0.354)	(0.359)	(0.349)	(0.354)
REP Donation% × Log(WFH)		0.812***				0.156***		
		(0.252)				(0.042)		
REP Donation% × High Risk			8.359***				1.241***	
			(1.911)				(0.387)	
REP Donation% × VHigh Risk				8.769***				1.615***
				(1.568)				(0.454)
Avg Loan Amount	0.852***	0.871***	0.862***	0.855***	0.749***	0.748***	0.748***	0.749***
	(0.079)	(0.077)	(0.078)	(0.080)	(0.083)	(0.082)	(0.082)	(0.082)
Avg Income Level	0.078	0.082	0.077	0.082	0.138	0.139	0.139	0.138
	(0.230)	(0.217)	(0.223)	(0.228)	(0.086)	(0.087)	(0.086)	(0.086)
Avg Male	-0.027	-0.029	-0.026	-0.027	0.033	0.034	0.035	0.034
	(0.061)	(0.060)	(0.061)	(0.067)	(0.035)	(0.035)	(0.035)	(0.036)
Avg White	-0.241*	-0.222*	-0.236*	-0.240*	-0.057	-0.057	-0.057	-0.057
	(0.122)	(0.113)	(0.119)	(0.122)	(0.035)	(0.035)	(0.035)	(0.035)
Log(#Tot Lender Applications)	0.048	0.046	0.047	0.048	0.175**	0.174**	0.174**	0.175**
	(0.049)	(0.047)	(0.048)	(0.048)	(0.077)	(0.077)	(0.077)	(0.077)
Observations	63,787	63,787	63,787	63,787	82,939	82,939	82,939	82,939
R-squared	0.906	0.907	0.907	0.906	0.906	0.906	0.906	0.906
First Lien	No	No	No	No	Yes	Yes	Yes	Yes
Jumbo	No	No	No	No	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Mortgage Interest Rate

This table presents the estimation results on the interest rates charged by lenders. The sample is at the mortgage level and includes conforming loans in the single-family loan performance data from Fannie Mae and Freddie Mac. The dependent variable, Interest Rate, is the mortgage interest rate charged by lenders. Zip represents the 3-digit zip code. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate	(4) Interest Rate
REP Donation%	0.005	0.003	0.013	0.016
	(0.198)	(0.210)	(0.202)	(0.201)
REP Donation% × Log(WFH)		0.001		
		(0.015)		
REP Donation% × High Risk			-0.063	
			(0.135)	
REP Donation% × VHigh Risk				-0.237
				(0.217)
Credit Score	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Debt to Income	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Loan to Value	0.007***	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
Unpaid Balance	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	12,376,170	12,376,170	12,376,170	12,376,170
R-squared	0.367	0.367	0.367	0.367
ZipCode-Year FE	Yes	Yes	Yes	Yes
Lender-ZipCode FE	Yes	Yes	Yes	Yes

Table 12: Loan Performance After Wildfires

This table presents the estimation results on mortgage delinquency after wildfire incidents. The sample is at the loan by year level and includes conforming loans in the single-family loan performance data from Fannie Mae and Freddie Mac. The dependent variable, Delinquent, is an indicator variable set to one if the mortgage is delinquent in the year. Zip represents the 3-digit zip code. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	(1) Delinquent	(2) Delinquent	(3) Delinquent	(4) Delinquent
Wildfire Impacted Area%	0.010***			
	(0.001)			
REP Donation% × Wildfire Impacted Area%		0.039*		0.018
		(0.020)		(0.023)
REP Donation%			-0.024	-0.024
			(0.017)	(0.017)
Credit Score			-0.000***	-0.000***
			(0.000)	(0.000)
Debt to Income			0.000***	0.000***
			(0.000)	(0.000)
Loan to Value			0.000***	0.000***
			(0.000)	(0.000)
Observations	48,677,259	48,677,259	48,677,259	48,677,259
R-squared	0.457	0.460	0.020	0.020
Loan FE	Yes	Yes	No	No
ZipCode-Year FE	No	Yes	Yes	Yes
Lender-ZipCode FE	Yes	No	Yes	Yes

Table 13: Alternative Types of Climate Risk

All samples are at the mortgage application level. The dependent variable, Approval, is an indicator variable set to one if the mortgage application is approved. Columns 1 to 3 represent mortgage applications that are second-lien and non-jumbo. Columns 4 to 6 represent mortgage applications that are jumbo and first-lien. SLR 5 Feet represents the percentage of land that will be submerged into the sea if the sea level rises by 5 feet. High Risk (Flooding) represents the percentage of land that is classified as high risk by the FEMA Flood map. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Second-Lien				Jumbo			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Approval	Approval	Approval	Approval	Approval	Approval	Approval	Approval
REP Donation%	0.286	0.220	0.249	0.235	0.069	0.066	0.044	0.037
	(0.260)	(0.282)	(0.248)	(0.278)	(0.126)	(0.122)	(0.148)	(0.147)
REP Donation% × SLR 5 Feet	7.767**			3.434	-0.256			-0.803
	(3.191)			(2.864)	(0.476)			(1.074)
REP Donation% × High Risk (Flooding)		0.932***		-0.011		0.008		0.110
		(0.239)		(0.323)		(0.052)		(0.076)
REP Donation% × High Risk (Wildfire)			1.741***	1.633***			0.136***	0.149
			(0.384)	(0.343)			(0.043)	(0.104)
Log(Loan Amount)	0.008	0.008	0.008	0.008	-0.045***	-0.045***	-0.045***	-0.045***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)	(0.005)	(0.005)
Income Level	0.166***	0.166***	0.166***	0.166***	0.394***	0.394***	0.394***	0.394***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.020)	(0.018)	(0.018)	(0.019)
Male	0.009***	0.009**	0.009***	0.009***	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)
White	0.097***	0.097***	0.097***	0.097***	0.010**	0.010**	0.010**	0.010**
	(0.006)	(0.009)	(0.006)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)
Log(#Tot Lender Applications)	0.009	0.009	0.008	0.008	-0.026	-0.026	-0.026	-0.026
	(0.007)	(0.007)	(0.006)	(0.006)	(0.016)	(0.016)	(0.017)	(0.017)
Observations	2,464,455	2,464,455	2,464,455	2,464,455	1,786,382	1,786,382	1,786,382	1,786,382
R-squared	0.191	0.191	0.192	0.192	0.118	0.118	0.118	0.118
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 14: Real Effects

This table examines whether the concentration of climate risk in Republican-leaning lenders has any real effects. The samples are at the county-year level. The first column represents the dependent variable of growth in real estate price. The second column represent local employment growth. The third column represents growth of local GDP. Republican-Leaning Bank Presence is calculated as the average REP Donation% weighted by the number of bank branches within the county. High Risk is the same wildfire risk defined earlier: fraction of land that is classified as high wildfire risk.

	(1) Real Estate Price Growth	(2) Employments Growth	(3) GDP Growth
Republican-Leaning Bank Presence	-0.008*	0.007	-0.019
	(0.005)	(0.008)	(0.015)
High Risk	-0.016	-0.024	0.002
	(0.024)	(0.016)	(0.089)
Republican-Leaning Bank Presence × High Risk	-0.005	-0.037	0.103
	(0.030)	(0.051)	(0.084)
Observations	15,893	12,446	12,446
R-squared	0.568	0.388	0.218
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

Appendix Figures and Tables

Figure A.1: Distribution of REP Donation%

This figure plots the histogram of the *REP Donation%* variable for the mortgage application sample.

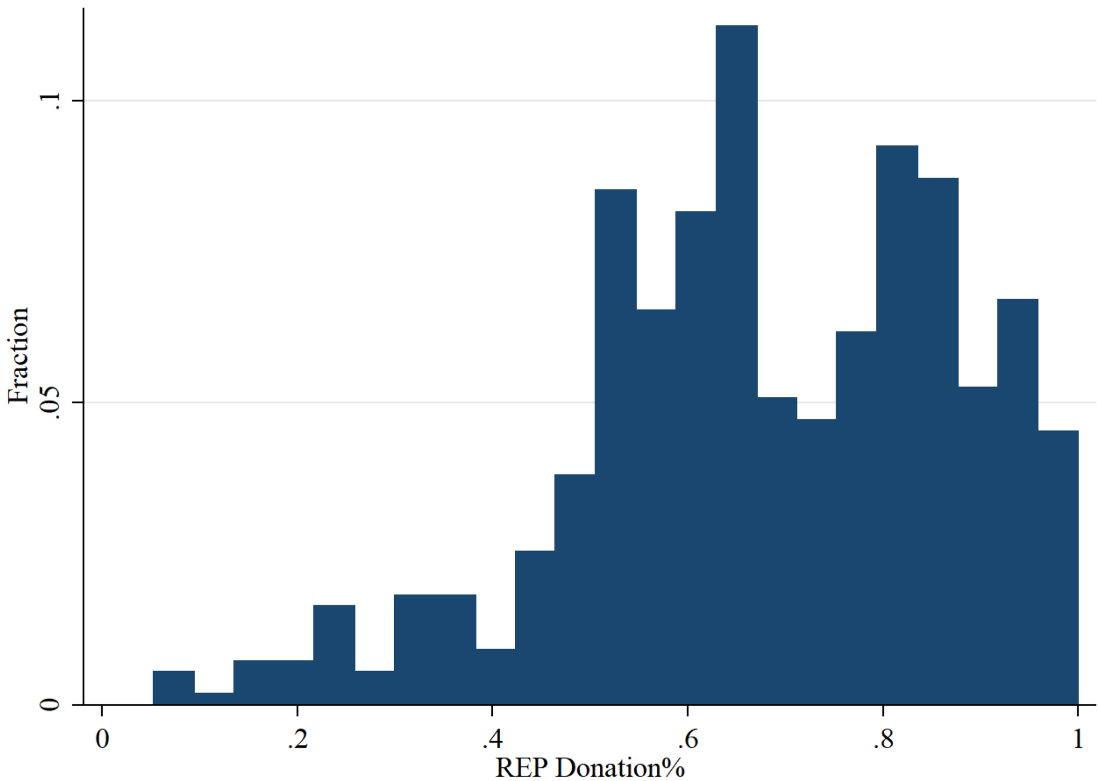


Table A.1: Variable Descriptions

(1) Variable Name	(2) Description	(3) Data Source
Log(WFH)	A county-year level variable. Calculated as the Log of the average of the continuous version of wildfire hazard risk. The continuous version of wildfire hazard risk takes a value from 0 to 100,000	WHP Map
High Risk	A county-year level variable. Calculated as the percentage of land that is classified as High or Very High wildfire risk.	WHP Map
VHigh Risk	A county-year level variable. Calculated as the percentage of land that is classified as Very High wildfire risk.	WHP Map
High Risk (Flooding)	A county-year level variable. Calculated as the percentage of land that is classified as High Flooding risk (code A or V).	FEMA Flood Map
SLR 5 Feet	A county-year level variable. Calculated as the percentage of land that will be submerged into the sea if the sea level rises by 5 feet.	NOAA Sea Level Rise
REP Donation%	A lender-year variable from 0 to 1, measuring the percentage of political donations made by lenders' PACs over the last two election cycles.	FEC Campaign Contribution
Climate Change Risk	A lender-quarter level variable that measures lenders' relative frequency of mentioning climate change together with risk on conference calls.	Sautner et al. (2020)
Climate Change Exposure	A lender-quarter level variable that measures lenders' relative frequency of mentioning climate exposure on conference calls.	Sautner et al. (2020)
Climate Change Sentiment	A lender-quarter level variable that measures lenders' sentiment when mentioning climate change on conference calls.	Sautner et al. (2020)
Approval	An indicator variable at the mortgage-application level indicating whether the mortgage application has been approved.	HMDA
Income Level	A category variable at the mortgage-application level indicating the income level of the mortgage applicants.	HMDA
Male	An indicator variable at the mortgage-application level indicating whether the mortgage applicant is male.	HMDA
White	An indicator variable at the mortgage-application level indicating whether the mortgage applicant is white.	HMDA
Log(Loan Amount)	A mortgage-application level variable. The log of the loan amounts associated with mortgage applications.	HMDA
Log(#Tot Lender Applications)	A lender-year level variable. The log of the number of total mortgage applications received by the lender in the previous year.	HMDA

Table A.1 (Continued)

(1) Variable Name	(2) Description	(3) Data Source
Hold	An indicator variable at the mortgage-loan level indicating whether the mortgage loan is sold in the secondary market. Only for approved applications.	HMDA
Collateral	An indicator variable at the mortgage-loan level indicating whether the mortgage application is denied because of collateral related reasons. Only for denied applications.	HMDA
Log(#app)	A lender-county-year level variable. The log of the number of total mortgage applications received by the lender in the county and year.	HMDA
Avg Loan Amount	A lender-county-year level variable. The average of Log(Loan Amount) at the lender-county-year level.	HMDA
Avg Income Level	A lender-county-year level variable. The average of Income Level at the lender-county-year level.	HMDA
Avg Male	A lender-county-year level variable. The average of Male at the lender-county-year level.	HMDA
Avg White	A lender-county-year level variable. The average of White at the lender-county-year level.	HMDA
Interest Rate	A loan level variable. The interest rate of the mortgage loans.	Fannie Mae and Freddie Mac
Delinquent	A loan-year level indicator variable, indicating whether the loan is going delinquent.	Fannie Mae and Freddie Mac
Credit Score	A loan level variable. The credit score of the borrower at loan origination.	Fannie Mae and Freddie Mac
Debt to Income	A loan level variable. The debt-to-income ratio of the borrower at loan origination.	Fannie Mae and Freddie Mac
Loan to Value	A loan level variable. The loan to value of the borrower at loan origination.	Fannie Mae and Freddie Mac
Unpaid Balance	A loan-year level variable, on the unpaid balance. ?	Fannie Mae and Freddie Mac
Republican-Leaning Bank Presence	A county-year level variable. The average REP Donation% weighted by the number of bank branches within the county.	FDIC Summary of Deposits
%Vote for Republican President	A county-year level variable. The fraction of vote for Republican presidents in the most recent presidential election.	MIT Election Lab
Real Estate Price Growth	A county-year level variable. Growth in real estate price.	Zillow
Employments Growth	A county-year level variable. Growth in local employment.	BEA
GDP Growth	A county-year level variable. Growth in local GDP.	BEA

Table A.2: Variable Correlations

This table presents pairwise correlations among variables. For detailed descriptions of the variables, see appendix Table A.1.

	(1) REP Donation%	(2) %Vote for Republican President	(3) ROE	(4) Log(Assets)	(5) Capital Ratio	(6) Log(#Tot Lender Applications)
REP Donation%	1					
%Vote for Republican President	0.28	1				
ROE	0.11	0.27	1			
Log(Assets)	-0.23	-0.12	0.05	1		
Capital Ratio	-0.03	-0.31	-0.46	-0.03	1	
Log(#Tot Lender Applications)	-0.08	0.06	0.03	0.68	0.13	1

Table A.3: Anecdote Examples on Mortgage Lenders' View toward Climate Risk

This table presents anecdotal evidence on whether mortgage lenders take climate risk into account. The examples are collected from SEC fillings.

(1) Lender	(2) Date of Filing	(3) Filing Type	(4) Quote
JPMorgan Chase	2/23/2021	10-K	... Climate-related physical risks include both acute weather events and chronic shifts in the climate. Potential physical risks from climate change may include altered distribution and intensity of rainfall, prolonged droughts or flooding, increased frequency of wildfires, rising sea levels, or a rising heat index....
Citigroup Inc	11/4/2020	10-Q	...Citigroup also has incorporated environmental factors like climate risk assessment and reporting criteria for certain obligors, as necessary. Factors evaluated include consideration of climate risk to an obligor's business and physical assets and, when relevant, consideration of cost-effective options to reduce greenhouse gas emissions...
Truist Financial Corp.	2/24/2021	10-K	...Deterioration in economic conditions, housing conditions or real estate values, including as a result of climate change or natural disasters, in the markets in which the Company operates could result in materially higher credit losses. The Company is also subject to physical risks, which could manifest in the form of asset quality deterioration and could be exacerbated by specific portfolio concentrations ...
PNC Financial Services	3/1/2019	10-K	. . . Climate change may be increasing the frequency or severity of adverse weather conditions, making the impact from these types of natural disasters on us or our customers worse. . .
Bank of America Corp.	2/24/2021	10-K	... the impact of climate change, such as rising average global temperatures and rising sea levels, and the increasing frequency and severity of extreme weather events and natural disasters such as droughts, floods, wildfires and hurricanes could negatively impact collateral, the valuations of home prices or commercial real estate or our customers' ability and/or willingness to pay outstanding loans... This could also cause insurability risk and/or increased insurance costs to customers...

Table A.4: Mortgage Approval Decisions

This table presents full estimations results of Table 3. All samples are at the mortgage application level. The dependent variable, Approval, is an indicator variable set to one if the mortgage application is approved. Panel A includes *second-lien* mortgage applications. Panel B includes *jumbo* mortgage applications. Panel C includes *conforming* mortgage applications. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Second-Lien	Approval	Approval	Approval	Approval	Approval	Approval	Approval
REP Donation%	0.331	-0.161	0.249	0.305	-0.293	0.211	0.298
	(0.268)	(0.243)	(0.248)	(0.261)	(0.196)	(0.260)	(0.277)
REP Donation% × Log(WFH)		0.171***			0.232***		
		(0.049)			(0.045)		
REP Donation% × High Risk			1.741***			2.634***	
			(0.384)			(0.401)	
REP Donation% × VHigh Risk				1.933***			3.283***
				(0.175)			(0.335)
Log(Loan Amount)	0.008	0.008	0.008	0.008			
	(0.010)	(0.010)	(0.010)	(0.010)			
Income Level	0.166***	0.166***	0.166***	0.166***			
	(0.008)	(0.008)	(0.008)	(0.008)			
Male	0.009***	0.009***	0.009***	0.009***			
	(0.003)	(0.003)	(0.003)	(0.003)			
White	0.097***	0.097***	0.097***	0.097***			
	(0.006)	(0.006)	(0.006)	(0.006)			
Log(#Tot Lender Applications)	0.009	0.007	0.008	0.008	0.016**	0.016**	0.017**
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)
Observations	2,464,455	2,464,455	2,464,455	2,464,455	2,464,455	2,464,455	2,464,455
R-squared	0.191	0.192	0.192	0.192	0.894	0.894	0.894
Similar Application FE	No	No	No	No	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.4 (Continued)

Panel B: Jumbo	(1) Approval	(2) Approval	(3) Approval	(4) Approval	(5) Approval	(6) Approval	(7) Approval
REP Donation%	0.067	-0.024	0.044	0.042	0.034	0.108	0.045
	(0.126)	(0.135)	(0.148)	(0.130)	(0.166)	(0.160)	(0.135)
REP Donation% × Log(WFH)		0.018***			0.022***		
		(0.001)			(0.006)		
REP Donation% × High Risk			0.136***			0.241**	
			(0.043)			(0.106)	
REP Donation% × VHigh Risk				0.333***			1.100***
				(0.021)			(0.152)
Log(Loan Amount)	-0.045***	-0.045***	-0.045***	-0.045***			
	(0.005)	(0.005)	(0.005)	(0.005)			
Income Level	0.394***	0.394***	0.394***	0.394***			
	(0.018)	(0.018)	(0.018)	(0.020)			
Male	0.002	0.002	0.002	0.002			
	(0.004)	(0.004)	(0.004)	(0.004)			
White	0.010**	0.010**	0.010**	0.010**			
	(0.004)	(0.004)	(0.004)	(0.004)			
Log(#Tot Lender Applications)	-0.026	-0.026	-0.026	-0.026	-0.034	-0.034	-0.033
	(0.016)	(0.016)	(0.017)	(0.016)	(0.021)	(0.021)	(0.021)
Observations	1,786,382	1,786,382	1,786,382	1,786,382	1,786,382	1,786,382	1,786,382
R-squared	0.118	0.118	0.118	0.118	0.918	0.918	0.918
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Similar Application FE	No	No	No	No	Yes	Yes	Yes

Table A.4 (Continued)

Panel B: Conforming	(1) Approval	(2) Approval	(3) Approval	(4) Approval	(5) Approval	(6) Approval	(7) Approval
REP Donation%	-0.132	-0.102	-0.131	-0.129	-0.103	-0.084	-0.070
	(0.151)	(0.133)	(0.150)	(0.151)	(0.107)	(0.107)	(0.107)
REP Donation% × Log(WFH)		-0.008			0.011		
		(0.006)			(0.012)		
REP Donation% × High Risk			-0.012			0.228**	
			(0.086)			(0.099)	
REP Donation% × VHigh Risk				-0.093			0.178
				(0.291)			(0.240)
Log(Loan Amount)	0.042***	0.042***	0.042***	0.042***			
	(0.008)	(0.008)	(0.008)	(0.008)			
Income Level	0.077***	0.077***	0.077***	0.077***			
	(0.008)	(0.008)	(0.008)	(0.008)			
Male	-0.003	-0.003	-0.003	-0.003			
	(0.002)	(0.003)	(0.003)	(0.002)			
White	0.060***	0.060***	0.060***	0.060***			
	(0.008)	(0.008)	(0.008)	(0.008)			
Log(#Tot Lender Applications)	-0.033	-0.033	-0.033	-0.033	-0.027	-0.027	-0.027
	(0.026)	(0.026)	(0.026)	(0.026)	(0.021)	(0.021)	(0.021)
Observations	19,288,215	19,288,215	19,288,215	19,288,215	19,288,215	19,288,215	19,288,215
R-squared	0.091	0.091	0.091	0.091	0.925	0.925	0.925
Jumbo Loan	No	No	No	No	No	No	No
First Lien	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Similar Application FE	No	No	No	No	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.5: Mortgage Approval Rate at Lender-County-Year level

This table presents the estimation results for lenders' mortgage approval decisions. The sample is at the lender-county-year level. The dependent variable, Approval Rate, is the lender-county-year level mortgage approval rate. Columns 1 to 3 represent mortgage applications that are second-lien and non-jumbo, and columns 4 to 6 include mortgage applications that are jumbo and first lien. Fixed effects specifications are indicated at the bottom of each panel. Standard errors double clustered by both property state and lender are reported in parentheses below the coefficients. *** p < 0.01, ** p < 0.05, * p < 0.1

	Second-Lien				Jumbo			
	(1) Approval Rate	(2) Approval Rate	(3) Approval Rate	(4) Approval Rate	(5) Approval Rate	(6) Approval Rate	(7) Approval Rate	(8) Approval Rate
REP Donation%	0.210	-0.150	0.156	0.196	0.087	-0.004	0.074	0.086
	(0.216)	(0.170)	(0.199)	(0.212)	(0.129)	(0.131)	(0.131)	(0.129)
REP Donation% × Log(WFH)		0.131***				0.023**		
		(0.038)				(0.009)		
REP Donation% × High Risk			1.342***				0.118**	
			(0.418)				(0.053)	
REP Donation% × VHigh Risk				1.872***				0.014
				(0.485)				(0.098)
Avg Loan Amount	0.011	0.012	0.011	0.011	-0.071***	-0.072***	-0.071***	-0.071***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.011)	(0.010)
Avg Income Level	0.157***	0.158***	0.157***	0.157***	0.385***	0.385***	0.385***	0.385***
	(0.016)	(0.015)	(0.016)	(0.016)	(0.020)	(0.020)	(0.022)	(0.021)
Avg Male	0.026**	0.027**	0.026**	0.026**	0.001	0.001	0.001	0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Avg White	0.081***	0.083***	0.082***	0.081***	0.005	0.005	0.005	0.005
	(0.016)	(0.016)	(0.016)	(0.016)	(0.013)	(0.013)	(0.013)	(0.013)
Log(#Tot Lender Applications)	0.004	0.004	0.004	0.004	-0.037**	-0.037**	-0.037**	-0.037**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.015)	(0.015)	(0.015)	(0.015)
Observations	56,609	56,609	56,609	56,609	45,243	45,243	45,243	45,243
R-squared	0.798	0.799	0.799	0.798	0.682	0.682	0.682	0.682
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.6: Specification with Different Years to Calculate *REP Donation%*

This table presents the estimation from Table 3 but with alternative specifications of REP Donation%, based on 3 years and 5 years.. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Second-Lien		Jumbo	
	(1) Approval	(2) Approval	(3) Approval	(4) Approval
REP Donation% (3 Years)	0.260		0.061	
	(0.220)		(0.107)	
REP Donation% (3 Years) × High Risk	1.350***		0.063	
	(0.353)		(0.039)	
REP Donation% (5 Years)		0.241		0.116
		(0.233)		(0.179)
REP Donation% (5 Years) × High Risk		1.860***		0.270***
		(0.418)		(0.072)
Log(Loan Amount)	0.009	0.008	-0.045***	-0.045***
	(0.010)	(0.010)	(0.005)	(0.005)
Income Level	0.166***	0.166***	0.395***	0.394***
	(0.008)	(0.008)	(0.019)	(0.019)
Male	0.009***	0.009***	0.002	0.002
	(0.003)	(0.003)	(0.004)	(0.004)
White	0.097***	0.097***	0.010**	0.010**
	(0.006)	(0.006)	(0.004)	(0.004)
Log(#Tot Lender Applications)	0.006	0.007	-0.025	-0.024
	(0.006)	(0.006)	(0.016)	(0.016)
Observations	2,464,455	2,464,455	1,784,881	1,786,382
R-squared	0.192	0.192	0.117	0.118
County-Year FE	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes

Table A.7: Excluding the Largest 10 Mortgage Lenders

This table presents the estimation of Table 3 but when the largest 10 mortgage lenders are excluded. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Second-Lien				Jumbo			
	(1) Approval	(2) Approval	(3) Approval	(4) Approval	(5) Approval	(6) Approval	(7) Approval	(8) Approval
REP Donation%	-0.108	-0.370	-0.127	-0.112	-0.124*	-0.122	-0.127	-0.113
	(0.177)	(0.244)	(0.178)	(0.177)	(0.068)	(0.105)	(0.084)	(0.076)
REP Donation% × Log(WFH)		0.123*				-0.000		
		(0.061)				(0.009)		
REP Donation% × High Risk			1.292***				0.020	
			(0.418)				(0.080)	
REP Donation% × VHigh Risk				1.702***				-0.162
				(0.256)				(0.100)
Log(Loan Amount)	0.009	0.009	0.009	0.009	-0.058***	-0.058***	-0.058***	-0.058***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.006)	(0.006)	(0.006)	(0.006)
Income Level	0.159***	0.159***	0.159***	0.159***	0.398***	0.398***	0.398***	0.398***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.015)	(0.015)	(0.016)	(0.015)
Male	0.005	0.005	0.005	0.005	-0.000	-0.000	-0.000	-0.000
	(0.004)	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
White	0.097***	0.097***	0.097***	0.097***	0.010***	0.010***	0.010***	0.010***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.002)	(0.003)	(0.003)	(0.003)
Log(#Tot Lender Applications)	-0.004	-0.003	-0.003	-0.003	-0.036***	-0.036***	-0.036***	-0.036***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)	(0.012)	(0.012)
Observations	866,699	866,699	866,699	866,699	497,977	497,977	497,977	497,977
R-squared	0.239	0.239	0.239	0.239	0.187	0.187	0.187	0.187
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.8: Poisson Estimation on the Number of Mortgage Applications

This table presents the same estimation as Table 9 but using a Poisson estimation, Cohn et al. (2021). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Second-Lien				Jumbo			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	#App.	#App.	#App.	#App.	#App.	#App.	#App.	#App.
REP Donation%	-0.240	-2.174	-0.421	-0.248	0.169	-0.971	-0.259	-0.068
	(0.997)	(1.437)	(1.017)	(0.998)	(0.622)	(0.698)	(0.668)	(0.633)
REP Donation% × Log(WFH)		0.684**				0.230***		
		(0.290)				(0.020)		
REP Donation% × High Risk			3.903				2.486***	
			(2.415)				(0.241)	
REP Donation% × VHigh Risk				0.634				3.232***
				(1.896)				(0.643)
Avg Loan Amount	-0.095	-0.086	-0.093	-0.095	-0.337**	-0.337**	-0.339**	-0.338**
	(0.141)	(0.144)	(0.142)	(0.141)	(0.171)	(0.171)	(0.171)	(0.171)
Avg Income Level	-0.265*	-0.255	-0.265*	-0.265*	0.405***	0.405**	0.403**	0.403**
	(0.160)	(0.156)	(0.159)	(0.160)	(0.157)	(0.164)	(0.161)	(0.161)
Avg Male	-0.034	-0.036	-0.035	-0.034	0.101*	0.102*	0.106**	0.103*
	(0.098)	(0.098)	(0.097)	(0.114)	(0.053)	(0.053)	(0.054)	(0.053)
Avg White	-0.087	-0.071	-0.086	-0.087	-0.118*	-0.113	-0.114	-0.115
	(0.100)	(0.098)	(0.099)	(0.110)	(0.070)	(0.074)	(0.084)	(0.083)
Log(#Tot Lender App.)	0.098	0.091	0.096	0.098	0.127	0.132	0.130	0.130
	(0.103)	(0.097)	(0.101)	(0.103)	(0.109)	(0.109)	(0.109)	(0.109)
Observations	92,340	92,340	92,340	92,340	96,325	96,325	96,325	96,325
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.9: With Bank-Year Call Report Controls

The table presents the estimation from Table 3 with bank-year level controls, including Log(Total Assets), ROE, and Capital Ratio. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Second-Lien				Jumbo			
	(1) Approval	(2) Approval	(3) Approval	(4) Approval	(5) Approval	(6) Approval	(7) Approval	(8) Approval
REP Donation%	0.517*	0.031	0.426	0.485*	0.042	-0.050	0.007	0.017
	(0.275)	(0.229)	(0.250)	(0.266)	(0.074)	(0.116)	(0.096)	(0.084)
REP Donation% × Log(WFH)		0.149***				0.019		
		(0.048)				(0.011)		
REP Donation% × High Risk			1.565***				0.195*	
			(0.333)				(0.109)	
REP Donation% × VHigh Risk				1.778***				0.332*
				(0.165)				(0.183)
Log(Loan Amount)	0.009	0.009	0.009	0.009	-0.041***	-0.041***	-0.041***	-0.041***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.004)	(0.004)	(0.005)	(0.005)
Income Level	0.167***	0.167***	0.167***	0.167***	0.404***	0.404***	0.404***	0.404***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.021)	(0.021)	(0.021)	(0.023)
Male	0.009***	0.009***	0.009***	0.009***	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
White	0.097***	0.097***	0.097***	0.097***	0.009**	0.009**	0.009*	0.009**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
ROE	0.231	0.191	0.210	0.209	0.056	0.059	0.058	0.058
	(0.367)	(0.342)	(0.344)	(0.357)	(0.135)	(0.134)	(0.135)	(0.135)
Capital Ratio	1.866**	1.238	1.675*	1.739**	1.201**	1.171**	1.181**	1.182**
	(0.830)	(0.808)	(0.834)	(0.840)	(0.461)	(0.467)	(0.463)	(0.465)
Log(Total Assets)	0.112	0.070	0.101	0.111	-0.013	-0.014	-0.013	-0.013
	(0.074)	(0.073)	(0.072)	(0.073)	(0.017)	(0.017)	(0.017)	(0.017)
Observations	2,423,487	2,423,487	2,423,487	2,423,487	1,636,762	1,636,762	1,636,762	1,636,762
R-squared	0.192	0.192	0.192	0.192	0.106	0.106	0.106	0.106
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.10: Census Tract FEs Instead of County as FEs

The table presents the estimation from Table 3 but with *Census Tract-Year* fixed effects and *Lender-Census Tract* fixed effects instead of *County-Year* fixed effects and *Lender-County* fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Second-Lien				Jumbo			
	(1) Approval	(2) Approval	(3) Approval	(4) Approval	(5) Approval	(6) Approval	(7) Approval	(8) Approval
REP Donation%	0.341	-0.208	0.246	0.311	0.078	-0.030	0.055	0.047
	(0.257)	(0.229)	(0.238)	(0.249)	(0.122)	(0.137)	(0.152)	(0.132)
REP Donation% × Log(WFH)		0.185***				0.021***		
		(0.051)				(0.002)		
REP Donation% × High Risk			1.817***				0.121*	
			(0.368)				(0.070)	
REP Donation% × VHigh Risk				2.024***				0.382***
				(0.192)				(0.057)
Log(Loan Amount)	0.002	0.002	0.002	0.002	-0.050***	-0.050***	-0.050***	-0.050***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
Income Level	0.156***	0.156***	0.156***	0.156***	0.400***	0.400***	0.400***	0.400***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.022)	(0.022)	(0.022)	(0.027)
Male	0.010***	0.010***	0.010***	0.010***	0.003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
White	0.086***	0.086***	0.086***	0.086***	0.008**	0.008**	0.008**	0.008**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.004)
Log(#Tot Lender Applications)	0.012*	0.009*	0.010*	0.011*	-0.024	-0.023	-0.024	-0.024
	(0.006)	(0.005)	(0.006)	(0.006)	(0.016)	(0.016)	(0.016)	(0.016)
Observations	2,464,455	2,464,455	2,464,455	2,464,455	1,786,382	1,786,382	1,786,382	1,786,382
R-squared	0.434	0.435	0.434	0.434	0.320	0.320	0.320	0.320
Census Tract-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes