How Climate Change Shapes Bank Lending:

Evidence from Portfolio Reallocation

Ralf R. Meisenzahl

March 30, 2023

WP 2023-12

https://doi.org/10.21033/wp-2023-12

FEDERAL RESERVE BANK of CHICAGO

How Climate Change Shapes Bank Lending: Evidence from Portfolio Reallocation*

Ralf R. Meisenzahl

March 30, 2023

Abstract

We document how bank lending has changed in response to climate change by analyzing changes in bank loan portfolios since 2012. Using supervisory data providing loan-level portfolios of the largest U.S. banks, we find that banks significantly reduced lending to areas more impacted by climate change starting around 2015. Using flood risk and wildfire risk as proxies for climate risk, we estimate a one standard deviation increase in climate risk reduces county-level balances in banks' portfolios by up to 4.7 percent between 2014 and 2020 in counties with large loan balances. The aggregate trend masks considerable heterogeneity. Banks reduced lending more for the riskier loans (HELOCs, CRE) and to borrowers with high credit risk. However, banks *expanded* lending, including riskier loans, to borrowers with the lowest credit risk in areas more impacted by climate change.

JEL Classification: G21

Keywords: Climate Change, Bank Lending, Portfolio Reallocation, Bank Risk Management.

*Ralf Meisenzahl (Ralf.Meisenzahl@chi.frb.org) is with the Federal Reserve Bank of Chicago. I thank Peter Sparks and Jonathan Yu for excellent research assistance. The views expressed here are those of the authors and do not necessarily reflect the views of the Board of Governors, the Federal Reserve Bank of Chicago or the staff of the Federal Reserve System.

1 Introduction

The 2014 UN climate summit and the 2015 Paris Agreement, which aimed to reduce emission to limit global temperature rise, threw climate risks into sharp relief. In the recent years, more severe and costly weather-related disasters have become more frequent. Four out of the six most costly weather-related disasters in the United States over the last 25 years occurred between 2017 and 2021.[1] As a result, losses for financial intermediaries, such as insurance companies and banks, related to weather-related events increased. Climate risk can therefore threaten the financial soundness of financial institutions. However, the Federal Reserve's 2020 Financial Stability Report cast doubt that banks have sufficiently granular information to determine potential losses.[2] Despite its importance, how financial intermediaries adjust their portfolios in response to climate risk has remained an open question.

In this paper, we analyze whether large U.S. banks reallocate credit provision in response to multiple types of climate risk. If banks are concerned about losses from extreme weather events, they should allocate credit away from higher climate risk areas to areas with lower climate risk. However, if losses are expected to be limited, for instance, due to insurance or government aid, such as disaster relief from the Federal Emergency Management Agency (FEMA), banks may not change their lending patterns.

To assess the banks' response to climate risks for loans to households and businesses, we use supervisory data from the Federal Reserve that provides the complete loan portfolio of the largest U.S. banks from 2009 to 2021. Loan-level portfolio information allows us to directly measure banks' exposures to high climate risk areas for multiple types of loans and to circumvent biases from loan sales and securitization that are inherent when using loan origination data. We combine the loan-level portfolio data with local climate risk data from FEMA, the National Oceanic and Atmospheric Administration (NOAA), and the National Risk Index (NRI). We focus on costal and river flood risk and wildfire risk as these cover the largest aera and were historically associated with the largest losses of climate change-related natural disasters.[3]

[1] Inflation-adjusted costs provided by NOAA, https://www.climate.gov/media/13978.

[2] See https://www.federalreserve.gov/publications/files/financial-stability-report-20201109.pdf,p.59 However, large U.S. banks submit climate action plans and report their progress, see Beltran et al. (2023).

[3] Much of the hurricane-related damage comes from flooding.

Our main analysis estimates the time-varying effect of county-level climate risk on loan balances and number of loans in the respective county. To account for bank conditions and bank-county matching, we saturate the model with bank-year and bank-county fixed effects. Choosing 2014, the year of the UN climate summit, as base year, we find no differences in residential mortgage balances between low and high flood risk areas after 2014. This result also holds for wildfire risk and is robust to using only river flood risk. However, for flood risk and wildfire risk, we find that the total number of mortgages held by banks decreased in high-risk areas relative to low-risk areas. A one-standard deviation increase in climate risk reduces the number of loans by up to 11.5 percent by 2020 compared to 2014. This finding is consistent with Ouazad and Kahn (2021) who find that more loans that can be securitized are approved after a weather-related disaster. Since the sample exhibits a heavily skewed distribution, we split the sample by average county-level balances and show that balances in counties with large average balances decline significantly more. This suggests that banks reduce their exposure in areas with high climate risk more if they have a sizable exposure in this area. The point estimate implies a reduction of 2.3 percent in mortgage balances in a high mortgage balance county with a one standard deviation higher flood risk. The overall pattern suggests that banks are holding fewer mortgages but with potentially larger mortgages in high-risk areas, indicating reallocation of credit between different borrower groups. Splitting the sample by exposure to mortgages in 2014, we find that the decline in the number of mortgages is driven by banks with ex-ante above-median exposure to mortgages. We also find some evidence that low capital banks retrenched more from high climate risk areas.

We then examine potential reallocation in more detail and split the mortgage lending by borrower credit score quartile. We find that banks' cut back on mortgages to borrowers in the lowest quartile of the credit score distribution. This group experiences a *reduction* in bank-held mortgage balances by almost one-third in areas with a one standard deviation higher flood risk between 2014 and 2020. At the same time, banks *expanded* their mortgage portfolio with higher mortgage balances from borrowers in the highest quartile of the credit score distribution in high-risk areas by 17.5 percent. The pattern also holds for the the number of loans and using wildfire risk. These findings are consistent with the literature. Specifically, recent studies show that mortgage credit supply to low credit score borrowers declines after flood zone changes and the authors attribute this effect to increased total costs of housing due to mandatory flood insurance (Sastry 2022; Blickle and Santos 2022). However, we also find a relative expansion of mortgage credit to high credit score borrowers by banks.

To be clear, these patterns show the banks' exposure to climate risk for the mortgages held on the balance sheet and not actual mortgage credit supply to the respective groups as mortgages can be sold and securitized.[4] However, the patterns indicate that banks are no longer willing to hold mortgages for low credit score borrowers, who are generally thought of as high-risk borrowers, if they live in areas with high climate risk, as in case of a weather-related disaster these borrowers, who tend to be financially or liquidity constrained, are more likely to miss payments and default, potentially increasing loan losses and/or administrative cost. In other words, climate risks compound borrower-specific risks. Our results indicate that banks reduce their exposures to these higher risk borrowers.

Next, we expand our analysis to other loan types. We start with home equity lines of credit (HELOCs). These residential real estate loans are riskier than mortgages as they are second-lien loans and less likely to be covered by insurance or disaster payouts and hence, we expect to find stronger effects of climate risk. We find a strong and statistically significant downward trend in HELOC balances and number of HELOC loans for flood risk and wildfire risk over the sample period. Areas with a one standard deviation climate risk experienced a relative decline in HELOC balance of up to 19.5 percent (number of loans: 13 percent) compared to the base county between 2014 and 2020. As for mortgages, this general trend masks considerable heterogeneity, with high credit score borrowers in high-risk areas experiencing a relative expansion of HELOC lending.

We then analyze banks' commercial loan portfolios, starting with commercial real estate. We find a negative, statistically significant effect of flood risk for all commercial real estate (CRE) loan balances. A one standard deviation increase in flood risk relatively reduces lending by 12 percent between 2014 and 2020. In contrast, we do not find any effect of flood or wildfire risk for the CRE number of commercial real estate loans in banks' portfolios. Splitting the sample by the type of commercial real estate, we document

[4] Sastry (2022) finds a decline of overall credit supply to low credit score and low income borrowers in Florida.

statistically significant negative effects of flood risk on lending to multifamily CRE loans and office building loans. These patterns are consistent with banks retrenching from areas with high climate risk, which increases the riskiness of borrowers in these areas. While there appears to be a relative downward trend for multifamily and office building lending in areas with higher wildfire risk, the effects are estimated imprecisely.

For loans to corporations (C&I) lending, we find a relative decline in loan balances in areas with higher climate risk for loans under $10 million to locally focused firms with loans after 2014. This finding is consistent with information-sensitive small business lending that implies that banks have considerable local knowledge about climate risk. There is also a relative downward trend in the number of loans for flood risk and wildfire risk. In counties within the top quartile of the C&I loan balance distribution, point estimates imply a reduction of 4.7 percent in lending for a one standard deviation increase in flood risk. Since liquidity provision by banks is crucial for firms to smooth temporary shocks, such as weather events (Brown, Gustafson, and Ivanov 2021), this finding suggests that firms in areas with higher climate risk are likely to be more financially constrained going forwards and may be less able to smooth temporary shocks.

In sum, our evidence indicates portfolio reallocation by banks away from riskier borrowers in areas with high loan balances and high climate risk. This finding has several implications. First, banks have been managing climate risk in their portfolios at least since 2014, alleviating some financial stability concerns stemming from climate change. Second, riskier borrowers in high climate risk areas may already face or will face credit supply constraints in the future. Third, climate risk may be concentrating in the shadow banking sector (see, e.g. Ivanov, Kruttli, and Watugala 2022) or in the government-sponsored enterprises that securitize mortgages (Ouazad and Kahn 2021; Gete and Tsouderou 2022).

We contribute to the literature on bank lending and climate change.[5] One strand focuses on the effect of flood insurance thresholds. Sastry (2022) and Blickle and Santos (2022) focus on changes in flood zones that increase insurance costs and find a reduction in mortgage lending and lower loan-to-value ratios after increases in flood risk measures. In contrast, we show that banks generally shift away from climate risk areas. A second

[5] For a broader survey on climate finance, see Giglio, Kelly, and Stroebel (2021).

strand of this literature has focused on sea level rise, house prices and lending. The (limited) effect of sea level rise on property values is well documented (Bernstein, Gustafson, and Lewis 2019; Baldauf, Garlappi, and Yannelis 2020; Murfin and Spiegel 2020). Nguyen et al. (2022) find that lenders charge higher interest rates on mortgages with higher sea level rise risk, while Keys and Mulder (2020) do not find differences in lender behavior such as credit denial. A third strand focuses on the consequences for high-emission firms. For instance, Javadi and Masum (2021) show that firms more exposed to climate risk pay higher interest rates.[6] In contrast, we examine how banks adjust their whole loan portfolio in response to climate risk and find, to some extent at odds with the 2020 Financial Stability report, that banks are sensitive to climate risks that compound borrower risks.

We also contribute to the literature on the composition of bank lending in response to a shock. Most of this literature has analyzed funding shocks (e.g., De Haas and Van Horen 2013; De Jonghe et al. 2019; Doerr and Schaz 2021), regulatory shocks (e.g., Auer, Matyunina, and Ongena 2022) or monetary policy shocks (den Haan, Sumner, and Yamashiro 2007). We expand this literature by analyzing how banks changed their loan portfolio in response to climate risk, which has became more salient after 2014.

The remainder of the paper is organized as follows. Section 2 provides an overview of the data. Section 3 presents the main analysis. We study heterogeneous effects by bank and borrower characteristics in section 4. Section 5 concludes.

2 Data

For our analysis, we match supervisory data on bank loan portfolio information from the Federal Reserve (Y-14) with sources reporting local climate exposures that we describe below.

2.1 Bank Loan Portfolio Data

We use the Federal Reserve's Y-14 data, a confidential supervisory loan-level dataset that is collected for the purpose of stress testing the largest U.S. bank holding companies.

[6] Degryse et al. (2023) document that "greener" firms paid less for syndicated loans after the 2015 Paris Agreement. Ivanov, Kruttli, and Watugala (2022) show that high-emission firms received less funding from banks.

The data includes information on 35 bank holding companies and spans 12 years. For each type of loan, we aggregated the outstanding loan balance and the number of outstanding loans to the bank-county-year level. For each bank we construct a balanced county-bank level panel by assuming that loan balances and loans are zero when we do not observe them in a county for a given year. We use the following loan type schedules of this dataset in our analysis:

Our commercial real estate data comes from Y-14Q schedule H.2. It contains all commercial real estate loans of at least one million dollars from the largest lenders, which are either held for investment or held for sale. It also contains smaller loans, if they are cross collateralized with at least one loan of at least one million dollars. We are using data from 2009 to 2019 as it contains more detail about loan information, which is necessary for our regressions. We also created subsets of the data using the building types of CRE loans, which in the dataset are office, retail, multifamily housing, and other.

Our corporate loan data comes from Y-14Q schedule H.1. It contains corporate loans and leases with a committed balance of at least 1 million dollars that are either held for investment or held for sale. The data was aggregated and filled in the same way as the H.2 data, except that our variable of interest in this case is committed exposure.

For mortgages we use the FR Y-14M schedule which starts in 2012. We restrict our attention to first lien mortgages that are serviced and held on the bank portfolio, as well as all home equity loans (HEL) and home equity lines of credit (HELOC).

Table 1 presents the summary statistics for the Y-19 data.

2.2 Climate Exposure data

We use measures of climate risk from the Federal Emergency Management Agency (FEMA). We have two main source: Flood maps, which are used for flood insurance rates, and the national risk index.

FEMA Flood Insurance rate maps

Our main flood data comes from the FEMA Flood Insurance rate maps (FIRMs). These maps have three main flood risk designations. The 100-year flood zone, which has at least a 1% annual chance of flooding, the 500-year flood zone, which has between a 0.2% and

1% annual flood risk, a low flood risk zones, which have a less than 0.2% annual flood risk. Homes that fall within a 100-year flood zone are generally required to purchase flood insurance. They notable omit rainfall-based flood risk in the maps but include the other major kinds of flood risk such as river overflow or oceanic.

These maps are shapefiles that are published at the county level. Maps are supposed to be updated at least every ten years; however, many maps are older than that especially in low flood risk and low population areas. We used these maps to create a census tract level dataset, which has the percentage area of the census tract that falls within each flood risk zone. This gives us a fine grain measure of flood risk as census tracts have populations of about 4000. We then aggregated this data up to include county level measures of flood risk, which is the average flood risk of each of the county's constituent census tracts.

It is also worth noting that FEMA's measure is more likely to underestimate than overestimate actual flood risk in a tract, as buildings are often clustered around coastlines and rivers, where the flood risk is generally higher.

National Risk Index

The National Risk Index (NRI) measures the risk due to 18 natural hazards.[7] The data comes from multiple sources, but mainly FEMA and NOAA. In additional to exposure to climate risk, the index also assess other factors that can increase or decrease the index. For instance, the index includes information on population exposed, building value exposed, and the probability of an extreme event occurring. We are using their measures for wildfire risk, coastal flooding, and river line flooding. Their risk index is a score from ranging from 0 to 100. We use the county level index.[8]

3 Empirical Analysis

In this section, we first describe our empirical methodology and then present the results for different loan types and different types of climate risks.

[7] For data and more details, see https://www.fema.gov/flood-maps/products-tools/national-risk-index.

[8] Census tract level information is also available.

3.1 Baseline Specification

We are interested in how banks respond to measures of climate risk. We expect the effect of climate risk to be time-varying as the debate about climate change intensified between 2010 and 2020 and extreme weather events became more frequent. Specifically, on September 23, 2014, the UN climate summit convened, drawing worldwide attention to the issue of climate change. We therefore use 2014 as our base year and we normalize the effect of climate risk on lending to 0 in 2014.[9]

$$y_{ijt} = \alpha_{ij} + \delta_{it} + \sum_t \beta_t * \text{Climate Risk}_j * year_t + \gamma X_{jt} + \varepsilon_{ijt} \tag{1}$$

where y_{ijt} is an outcome variable of interest relating to characteristics of bank i's portfolio in county j in year t. These outcome variables include outstanding loan balances and the number of loans for different types of loans in the portfolio. X is a vector of county controls that include wages. We also include bank-county fixed effects α_{ij} to account for bank-county matching and bank-year fixed effects δ_{it} to account for time-varying bank conditions. We are interested in β_t, the coefficient for year t on our static measure of county climate risk (invariant across time) interacted with year dummies. All standard errors were clustered at the bank-county and bank-year level.

There are two shortcomings to this approach. The first is that we use a publicly available measure of climate risk that may not be the measure a specific bank uses. This mismeasurement would attenuate the estimated effects. Second, we use climate risk measures as of 2021, rather than the historical climate risk assessments. This may also introduce mismeasurement as, on net, the risks increased between 2010 and 2021. However, we take the most recent climate risk measurement to potentially capture anticipation effects or more real time assessments than the publicly available measures in the respective year as some of the public information is stale.

[9]Consistent with the importance of the 2014 UN climate summit, normalized google trends for climate change searches spiked in 2014. See figure A1 in Appendix A.

3.2 Results for Residential Real Estate Loans

Mortgages

We start our analysis with changes in residential mortgage lending over time with flood risk as the climate risk measure. The effect of flood risk on mortgages in bank balance is unclear as mandatory flood insurance and FEMA disaster relief reduce the likelihood of losses on mortgages due to floods. At the same time, pre-payment risk increases due to disasters, potentially reducing incentives to hold mortgages that were originated in high flood risk areas.

Figure 1, panel a) shows the results of estimating equation 1 with the county-level mortgage balances of a bank in a given year as the dependent variable. While there is a downward trend in mortgage lending to counties with higher flood risk over the sample period, the estimated effect is statistically not different from 0. One concern is that coastal areas, which experienced significant increases in housing demand over the sample period, may be driving this result. When we restrict the sample to non-coastal counties and use only river flood risk, we find similar results (see Appendix A).

In panel b), we repeat the analysis with wild fire risk from the National Risk Index. Due to the potentially outsized effect of counties in California that experienced significant wildfires during the sample period, we drop California from the baseline. While there appears to be a negative trend pre-2020, the point estimates are small and not statistically significant.[10]

Panel c) shows the results for the number of mortgages and flood risk. We find a negative trend after 2014. The point estimates are statistically significant from 2016 on. In terms of economic magnitude, we are comparing two counties, one with average flood risk and one with a one standard deviation higher flood risk. The estimate implies that, compared to 2014, the county with a one standard deviation higher flood risk (3.22) experienced a relative reduction in the number of mortgages held by each bank by 6.3 or 8 percent in 2020.[11]

Panel d) shows the results for the number of mortgages with wildfire risk. As for

[10]When we including California find a small, significant upward trend in overall mortgage balances in areas with higher wildfire risk relative to areas with lower wildfire risk over time (see Appendix Figure A4).

[11]We find similar results are river flooding only (see Appendix A).

flood risk, we find a negative trend after 2014 and the overall contour is similar to the flood risk results. The point estimates are statistically significant from 2017 on. The estimate implies that, compared to 2014, a county with a one standard deviation higher wildfire risk (6.26) experienced a relative reduction in the number of mortgages held by each bank by 7.5 or 11.5 percent in 2020.[12]

One caveat to these results is that the effect is estimated across all counties, including many counties with small exposures (see Table 1). However, to understand to what extent climate risk poses a threat to financial stability, we focus on counties in which banks have large exposure. We therefore split the sample in counties with small and counties with large exposure measures. Large exposures are defined as counties with an average county-level mortgage balance being in the 75th percentile of the distribution ($2.79 mill).

Figure 2 shows the results of this sample split with flood risk as the measure for climate risk. Comparing the results for mortgage balances for large (panel a) and small mortgage balance counties (panel b), we find that only negative and statistically significant coefficient for large counties, suggesting that the insignificant effects reported in Figure 1, panel a) are driven by counties with small mortgage balances. In terms of economic significance, we find that a one-standard deviation increase in flood risk relatively reduced mortgage balances by about $0.5 mil between 2014 and 2019 or about 2.3 percent. Similarly, we find a relative reduction in the number of loans by about 2 loans or 2.6 percent. We find comparable results when restricting the sample to the top 10 percent of counties by average mortgage balances.

Taken together, the results suggest that banks retained fewer mortgages that were originated in high climate risk areas and, for counties with large mortgage balances a reduction in mortgages on banks' balance sheets. We examine which borrowers are experiencing the largest reduction in bank mortgage lending in section 4.

HELOCs

Next, we examine riskier loans backed by residential real estate: home equity lines of credit. These loans are subordinated to mortgages and may not be fully covered by flood

[12] The results for river flooding only are comparable, see Appendix A.

insurance or FEMA disaster relief. Hence, we expect that if banks reduce their exposure to climate risk, they should reduce HELOC lending in areas with high climate risk.

Figure 3, panel a) shows the results of estimating equation 1 with county-level HELOC balances of a bank in a given year as the dependent variable and flood risk as the climate risk measure. There is a downward trend in mortgage lending to counties with higher flood risk over the sample period. While the estimated effect is only marginally significant in 2016 and 2017, the estimated effect increases in magnitude and is significant for the last four years. In 2020, the estimate effect implies that, compared to 2014, a county with a one standard deviation higher flood risk (2.12) experienced a relative bank-level reduction in HELOC balances by $129k or 3.2 percent.

Panel b) shows the results for HELOCs balances with wildfire risk as the climate risk measure. As above we exclude California in the baseline with wildfire risk and report the results including California in the appendix. Similar to the flood risk results, we find a negative trend after 2014. The point estimates are statistically significant from 2017 on and are somewhat more precisely estimated than the coefficients on flood risk. Compared to 2014, a county with a one standard deviation higher wildfire risk experienced a relative bank-level reduction in HELOC balances by 19.5 percent in 2020.

Panel c) shows the results for the number of HELOCs and flood risk. Consistent with lower balances, we find a negative trend after 2014 with statistically significant point estimates from 2016 on. Compared to 2014, a county with a one standard deviation higher flood risk experienced a relative bank-level reduction in the number of HELOCs by 5 percent in 2020.

Panel d) shows the results for the number of HELOCs and wildfire risk. Similar to the flood risk results, we find a negative trend after 2014 with statistically significant point estimates from 2017 on. Compared to 2014, a county with a one standard deviation higher flood risk experienced a relative bank-level reduction in the number of HELOCs by 13 percent in 2020.

When splitting the sample in counties with high and low balances, in parallel to the mortgage regressions, we find no effect on balances in large balance counties and a negative effect on balances in small counties. However, both groups exhibit a downward trend in the number of HELOC loans.[13]

In sum, banks reduced their exposure to climate risk in riskier residential real estate loans by reducing the total balances outstanding and the number of loans. This finding is consistent with banks reducing exposure to riskier loans first. Below we assess which borrower groups in high climate risk areas are most affected by this reduction in HELOC lending.

Commercial Real Estate (CRE) Loans

We now turn to lending backed by commercial real estate. These loans tend to be riskier to the extent that they are much larger loans compared to residential mortgages. Hence, we expect banks to reduce their lending to commercial real estate in areas with high climate risk.

Figure 4 shows the results of estimating equation 1 with county-level CRE balances and loans held by a bank in a given year as dependent variable and both climate risk measures. We see a statistically significant relative reduction in CRE loan balances in areas with high flood risk (panel a) after 2014 but not in areas with high wild fire risk (panel b).[14] A one standard deviation increase in flood risk relatively reduces CRE lending in the area with higher flood risk by about \$5 mill or about 12 percent of the sample mean between 2014 and 2019. The larger point estimates and confidence intervals for 2020 reflect the period of shutdowns during the COVID-19 pandemic that significantly reduced lending to CRE in general and should be interpreted with caution. For the number of loans, we find negative but insignificant point estimates after 2014.

It is useful to consider different types of commercial real estate. Specifically, we estimate the regressions on the subsample of multi-family housing and the subsample of office loans. Figure 5 shows that a significant relative reduction in lending in areas with high flood risk by 2019 (panels a and c), but no significant effects for wildfire risk (panels b and d) for both mulit-family and office lending.

Commercial and Industrial (C&I) Loans

Last, we investigate C&I loans, especially loans to smaller firms as they are often thought of as more information-intensive. Hence, these loans tend to be extended by banks that

[13] The results are reported in Appendix A, Figure A3.

[14] As for residential mortgages, the baseline wildfire risk regressions drop all counties in California.

have considerable local information. At the same time, locally focused firms' default risk is often linked to local economic conditions. We therefore restrict the sample to the subset of loans under \$10 million.[15] This restriction avoids attributing the climate risk large firms' headquarters are exposed to with the exposure of the whole firm. Unfortunately, the Y-14 data only include loans to firms over \$1 million, meaning the sample does not include the firms most dependent on and most vulnerable to local conditions.

Figure 6 shows the results for C&I loans. We find that C&I loan balances declined from 2014 to 2020 in areas with either higher flood risk or higher wildfire risk compared to areas with low climate risk (panel a and c). A one standard deviation increase in flood risk relatively reduces C&I lending under \$10 mill in the area with higher flood risk by about \$0.8 mill or about 3 percent of the sample mean over this time period. We find negative effects of climate risk on the number of loans after 2014, but these estimates are only marginally statistically significant.

When splitting the sample by size of the county-level C&I balances, we find negative and significant effects of flood risk over time on balances and number of loans for large balance counties only. A large balance county with a one standard deviation higher flood risk experienced a relative reduction in C&I loan balances by 4.7 percent and a reduction in the number of loans by 3.4 percent. For small C&I balance counties, we find a marginally significant but small increase in balances and in the number of loans (see Appendix, Figure A6).

In sum, we find that banks retrenched from areas with higher climate risk across all longer-term loan types after the 2014 UN Climate Summit. Given that we use 2021 climate risk measures, the findings indicate that banks may have adjusted their portfolios in part in anticipation of higher climate risk.

4 Heterogeneous Effects

In this section, we analyze whether the relative reduction in lending due to climate risk is driven by specific bank characteristics and whether it is affecting all borrowers equally. We start with bank characteristics and then analyze differences by borrower

[15] We report the results for all loans in Appendix A. We overall contour of the results is the same, though the coefficients are less precisely estimated.

risk. For C&I and CRE loans, we lack comprehensive risk assessments and therefore focus on residential real estate loans in this section.

4.1 Bank Heterogeneity

We expect banks with larger exposures and lower loss-absorbing capacity to decrease lending relatively more. Banks that are more exposed for residential mortgages face on average larger expected losses from climate risk, and banks that have lower capital have less capacity to absorb higher expected losses from climate risk. To test whether more exposed and low capital banks have been reducing lending more, we split the sample by above- and below-median mortgages-to-asset ratios and capital-to-asset (leverage) ratios as of 2014 and then estimate equation 1 for each subsample.[16]

Figure 7, panels a) and b) shows the mortgage regression results, splitting the sample by exposure to residential mortgages. The results reported in section 3 are mostly driven by banks with above-median exposure to mortgages. These banks reduced lending in high climate risk areas relative to low climate risk areas significantly more since 2014.[17] Indeed, the estimates effects for below-median exposure banks are often only statistically significant at the 10 percent level and in most cases statistically different from the effects estimated for above-median exposure banks.

Figure 7, panels c) and d) show the results for HELOCs. While we find little differences by mortgage exposure for flood risk, we see significant differences for wildfire risk that are in lines with the mortgage results.[18] Taken together, the findings suggests that banks with more exposure to climate risk through mortgages reduced lending in high climate risk areas relatively more.

Next, we turn to loss-absorbing capacity and split the sample by above- and below-median capital-to-asset (leverage) ratio. Figure 8, panels a) and b) show the results for mortgages. Consistent with banks with less loss-absorbing capacity retrenching more, we find that banks with below-median leverage ratios reduced lending relatively more in areas with higher climate risk. However, we do not find any differences in HELOC

[16]We use the leverage ratio because in the case of climate risk, risk-weighted assets could be misleading if climate risks are not fully considered in the risk weights.

[17]We find similar results for mortgage balances, see Appendix figure A7, panels a) and b).

[18]HELOC balances exhibit the same pattern, see Appendix.

lending patterns between low and high capital banks (panels c and d).[19]

The sample splits by bank characteristics indicate that after 2014, when climate risk was thrown in sharp relief, banks that were relatively more exposed to climate risk started to reduce their relative exposure to climate risk more than their less exposed peers. This finding is consistent with banks reducing risk in their portfolios when having significant exposures or low loss-absorbing capacity.

4.2 Borrower Heterogeneity

Having shown that banks with more exposure to climate risk reduced lending more, we also expect that if banks are concerned about loan losses, banks would reduce credit supply to the borrowers most financially vulnerable to climate events as such borrowers are less likely to be able to repay their loans. For households, we use the bank-reported credit score as a measure of risk and for corporate borrowers the bank-reported probability of default. We restrict the data to counties with at least 80 loans to ensure the robustness of our quartiles.

To analyze heterogeneous effects of climate risk by borrower risk, we take the bank-level credit score distribution in 2014 and fix the quartiles of this distribution. We then compute total balances and number of loans at the bank-county-credit score quartile-year level. We add the triple interaction of climate risk, year and credit score quartile as well as the lower interaction to the baseline regression. The base category is the second quartile. As before, we flexibly control for bank-year and bank-county using fixed effects and double-cluster the standard errors on the bank-year and bank-county level.

Figure 9, panel a) shows the result for the highest and lowest credit score groups' mortgage balances with flood risk as measure of climate risk and panel b) shows the results for the wildfire risk. Panels c) and d) repeat the regressions with the number of loans as dependent variables. The figures show that in terms of balances and number of loans, borrowers in the highest quartile of the credit score distribution in counties with higher flood risk experience a expansion of credit over time relative to the same credit score borrowers in counties with lower flood risk. In contrast, borrowers in lowest quartile of the credit risk distribution in counties with high flood risk experiences a contraction

[19] We find no differences for mortgage balance and small differences for HELOC balances, see Appendix.

in credit supply over time relative to their peers in counties with lower flood risk. In terms of economic magnitudes, a one standard deviation increase in flood risk relatively reduces mortgage balances by 33% of the mean county-level balance and the number of loans by 17.5% for the highest credit risk-lowest credit score quartile, while balances and number of loans increase by 18% and 14%, respectively, for the lowest risk-highest credit score quartile. The patterns hold when restricting the sample to above-median balance counties and to counties in the 75th percentile of the balance distribution.[20]

We find the same pattern when we estimate the same regression with HELOC balances and number of loans (Figure 10). This finding suggests a significant reallocation in banks' residential real estate loan portfolios away from low credit score borrowers exposed to climate risk towards either higher credit score borrowers exposed to the same climate risk or comparable borrowers not exposed to climate risk. In other words, banks continue to hold mortgages and HELOCs that were originated in areas with high(er) climate risk but concentrate on borrowers with higher credit scores. This is consistent with loss mitigation necessary due to climate change, as high credit score borrowers are more likely to be in a position to handle financial shocks such as extreme weather events and therefore are less likely to default.

5 Conclusion

We document that banks have started to shift their portfolios away from areas with high climate risk starting after the 2014 UN Climate Summit. This shift is driven by a relative reduction in lending to the borrowers more vulnerable to climate shocks. These findings suggest that banks are concerned about potential losses from more frequent extreme weather events and manage this risk accordingly, limiting the financial stability concern of climate change originating in the regulated banking sector. Blickle and Santos (2022) provides some evidence that an increase in flood risk increases mortgage securitization. Further research should therefore assess whether nonbank lenders substitute for the reduction in bank credit and hence have an increased exposure to climate risks that could threaten financial stability.

[20] We also find the same pattern for below-median balance counties.

References

Auer, Raphael, Alexandra Matyunina, and Steven Ongena. 2022. “The countercyclical capital buffer and the composition of bank lending.” *Journal of Financial Intermediation* 52:100965.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis. 2020. “Does Climate Change Affect Real Estate Prices? Only If You Believe In It.” *Review of Financial Studies* 33 (3):1256–1295.

Beltran, Daniel O., Hannah Bensen, Amy Kvien, Erin McDevitt, Monica V. Sanz, and Pinar Uysal. 2023. “What are Large Global Banks Doing About Climate Change?” Working Paper 1368, Federal Reserve Board.

Bernstein, Asaf, Matthew T. Gustafson, and Ryan Lewis. 2019. “Disaster on the horizon: The price effect of sea level rise.” *Journal of Financial Economics* 134 (2):253–272.

Blickle, Kristian S. and Joao A. C. Santos. 2022. “Unintended Consequences of Mandatory Flood Insurance.” Working paper, Federal Reserve Bank of New York.

Brown, James R., Matthew T. Gustafson, and Ivan T. Ivanov. 2021. “Weathering Cash Flow Shocks.” *Journal of Finance* 76 (4):1731–1772.

De Haas, Ralph and Neeltje Van Horen. 2013. “Running for the Exit? International Bank Lending During a Financial Crisis.” *Review of Financial Studies* 26 (1):244–285.

De Jonghe, Olivier, Hans Dewachter, Klaas Mulier, Steven Ongena, and Glenn Schepens. 2019. “Some Borrowers Are More Equal than Others: Bank Funding Shocks and Credit Reallocation.” *Review of Finance* 24 (1):1–43.

Degryse, Hans, Roman Goncharenko, Carola Theunisz, and Tamas Vadasz. 2023. “When green meets green.” *Journal of Corporate Finance* 78:102355.

den Haan, Wouter J., Steven W. Sumner, and Guy M. Yamashiro. 2007. “Bank loan portfolios and the monetary transmission mechanism.” *Journal of Monetary Economics* 54 (3):904–924.

Doerr, Sebastian and Philipp Schaz. 2021. “Geographic diversification and bank lending during crises.” *Journal of Financial Economics* 140 (3):768–788.

Gete, Pedro and Athena Tsouderou. 2022. “Climate Risk in Mortgage Markets: Evidence from Hurricanes Harvey and Irma.” Working Paper 3961832, SSRN.

Giglio, Stefano, Bryan Kelly, and Johannes Stroebel. 2021. “Climate Finance.” *Annual Review of Financial Economics* 13 (1):15–36.

Ivanov, Ivan, Mathias S. Kruttli, and Sumudu W. Watugala. 2022. “Banking on Carbon: Corporate Lending and Cap-and-Trade Policy.” Working Paper 3650447, SSRN.

Javadi, Siamak and Abdullah-Al Masum. 2021. “The impact of climate change on the cost of bank loans.” *Journal of Corporate Finance* 69:102019.

Keys, Benjamin J and Philip Mulder. 2020. “Neglected No More: Housing Markets, Mortgage Lending, and Sea Level Rise.” Working Paper 27930, National Bureau of Economic Research.

Murfin, Justin and Matthew Spiegel. 2020. “Is the Risk of Sea Level Rise Capitalized in Residential Real Estate?” *Review of Financial Studies* 33 (3):1217–1255.

Nguyen, Duc Duy, Steven Ongena, Shusen Qi, and Vathunyoo Sila. 2022. “Climate Change Risk and the Cost of Mortgage Credit*.” *Review of Finance* 26 (6):1509–1549.

Ouazad, Amine and Matthew E Kahn. 2021. “Mortgage Finance and Climate Change: Securitization Dynamics in the Aftermath of Natural Disasters.” *Review of Financial Studies* 35 (8):3617–3665.

Sastry, Parinitha. 2022. “Who Bears Flood Risk? Evidence from Mortgage Markets in Florida.” Working Paper 4306291, SSRN.

Figures and Tables

Table 1
Summary Statistics

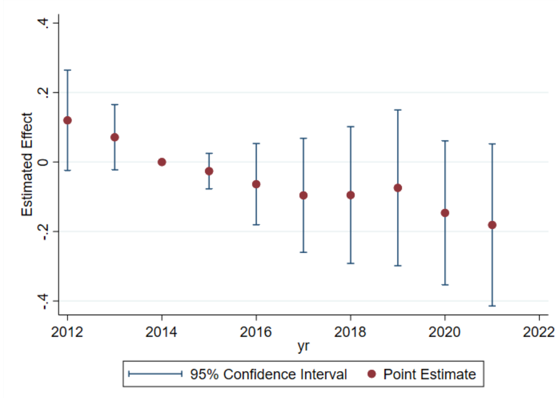
This table provides the summary statistics for the analysis. We aggregate loan-level data to the bank-county-year level.

	N	Mean	SD	25p	median	75p
Mortgage Balances (in mill)	528,620	23.11	270.91	0	0.36	2.29
Mortgage Loans	528,620	79.44	535.66	0	3	20
Flood risk (Percentage Points)	528,620	2.12	3.34	0.36	1.19	2.69
Wildfire risk (Percentage Points)	528,620	6.92	10.11	1.43	3.10	8.15
HELOC Balances (in mill)	404,260	8.44	70.25	0	0.11	1.15
HELOC Loans	404,260	176.47	1071.17	0	4	32
CRE Balances (in mill)	87,622	46.41	247.72	1.12	5.26	25
CRE Loans	87,622	6.69	35.68	1	1	4
Office Loan Balances (in mill)	24,341	49.31	185.25	2.30	8.42	32.49
Office Loans	24,341	4.33	10.53	1	2	4
Multi-Family Balances (in mill)	34,323	54.29	530.18	1.87	8.06	29.07
Multi-Family Loans	24,323	40.85	186.64	1	2	3
C&I Loan Balances (in mill)	182,564	31.99	192.75	1.48	5.76	17.24
C&I Loans	182,564	13.12	106.22	1	2	6

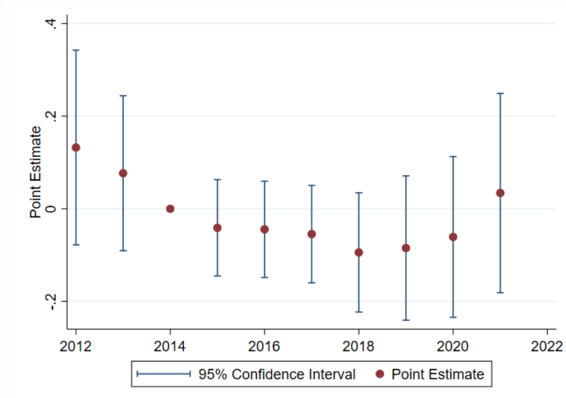
Figure 1: Mortgage Balances in Banks' Portfolios

This figure shows the results of estimating equation 1 with mortgage balances (in millions) in panels a) and b) and with number of loans in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Mortgages Balances

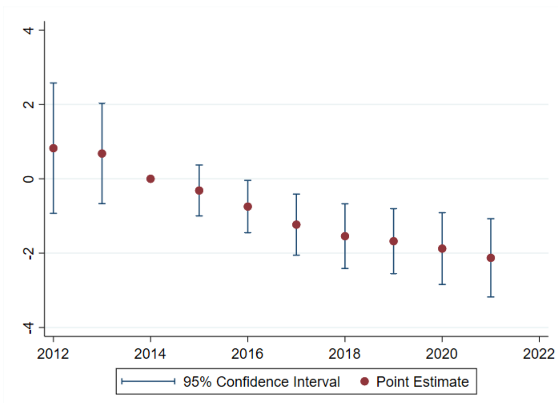


a) Flood Risk

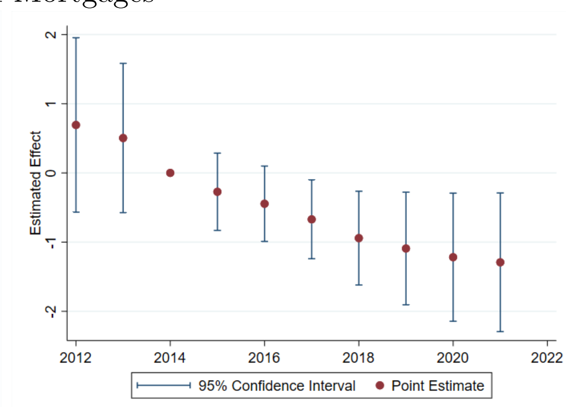


b) Wildfire Risk

Number of Mortgages



c) Flood Risk

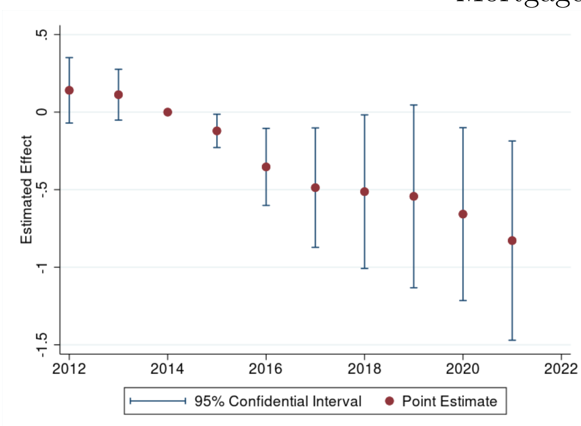


d) Wildfire Risk

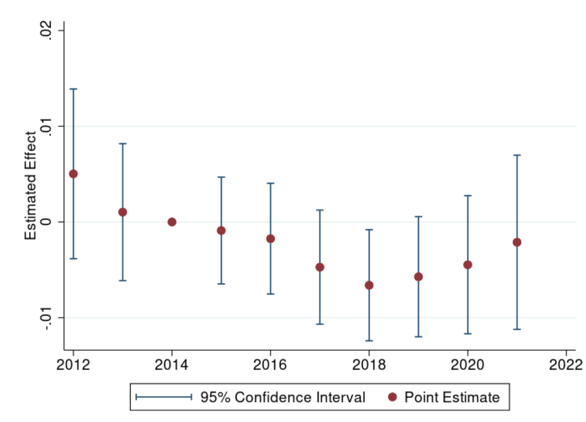
Figure 2: Mortgage Balances - County Exposure Split (Flood Risk)

This figure shows the results of estimating equation 1 with mortgage balances (in millions) in panels a) and b) and with number of loans in panels c) and d) as dependent variables. Large balance-counties are counties in the 75th percentile of the mortgage balance distribution. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Mortgages Balances

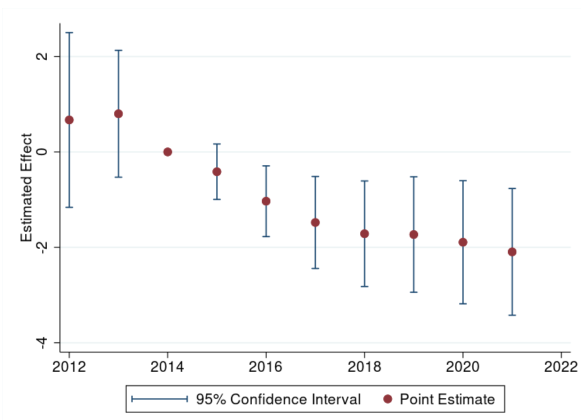


a) Large Balances

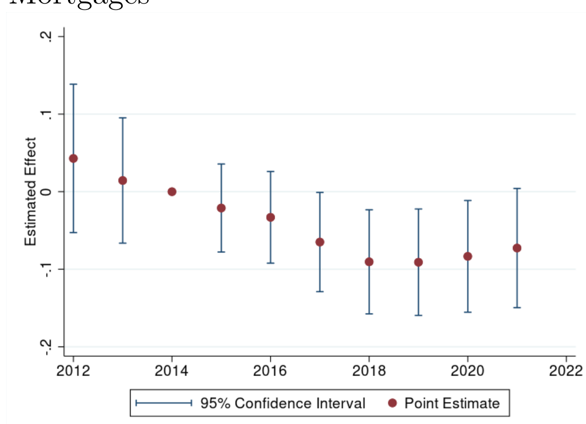


b) Small Balances

Number of Mortgages



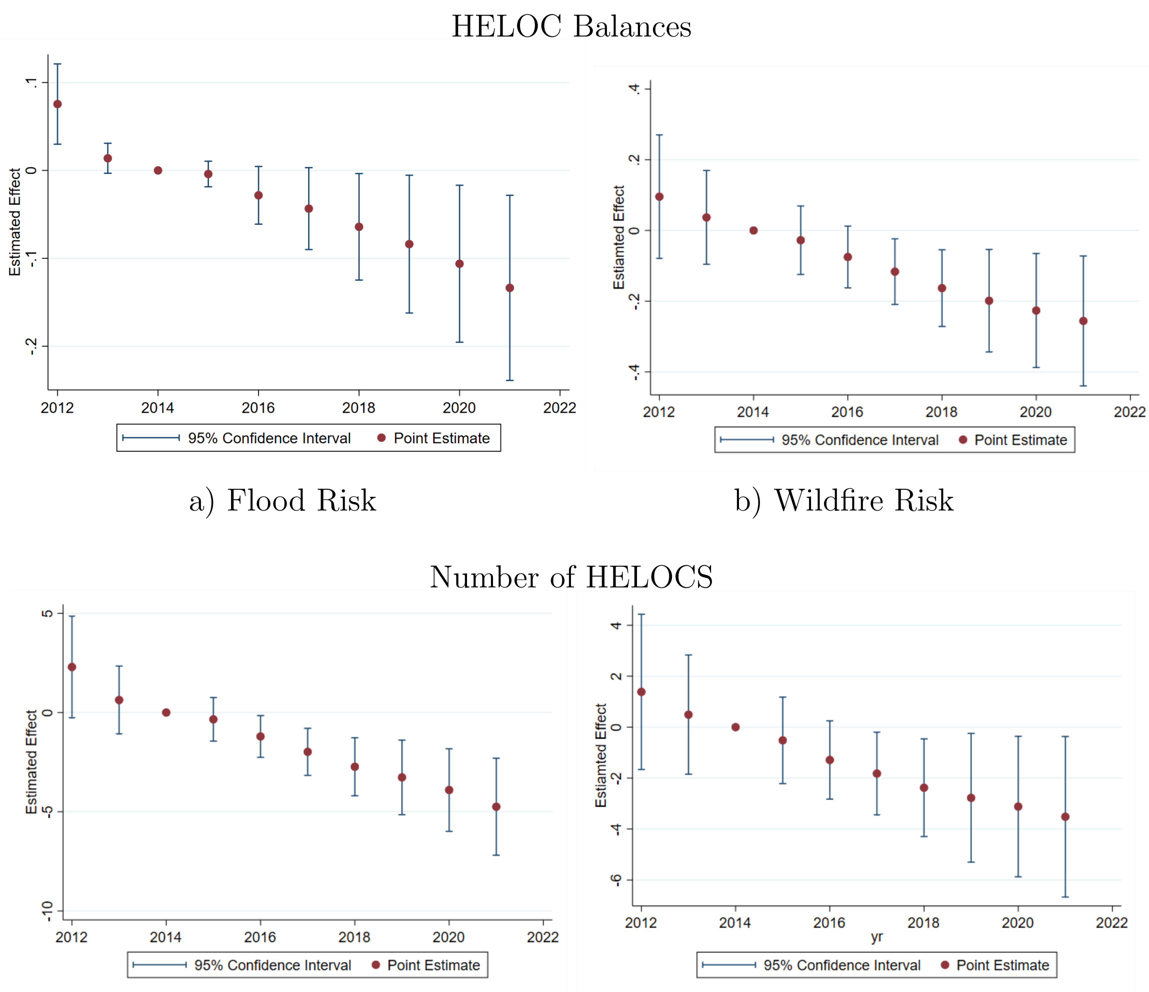
c) Large Balances



d) Small Balances

Figure 3: HELOCs in Banks' Portfolios

This figure shows the results of estimating equation 1 with HELOC balances (in millions) in panels a) and b) and with number of loans in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.



a) Flood Risk

b) Wildfire Risk

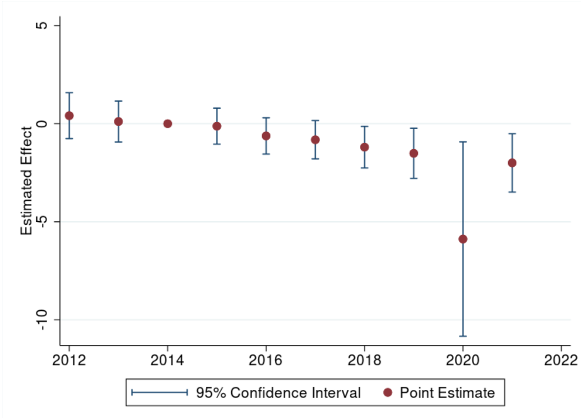
c) Flood Risk

d) Wildfire Risk

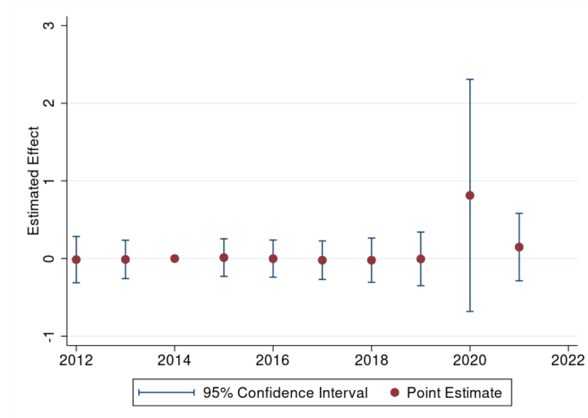
Figure 4: Commercial Real Estate Loans in Banks' Portfolios

This figure shows the results of estimating equation 1 with CRE balances (in millions) in panels a) and b) and with number of loans in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

CRE Loan Balances

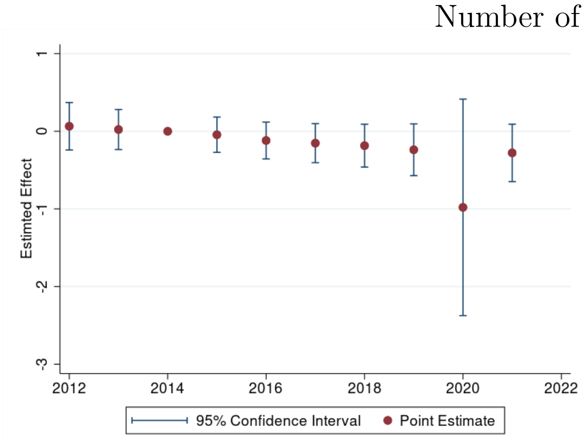


a) Flood Risk

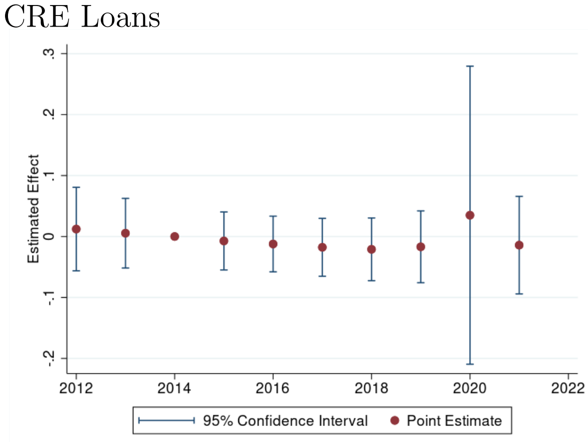


b) Wildfire Risk

Number of CRE Loans



c) Flood Risk

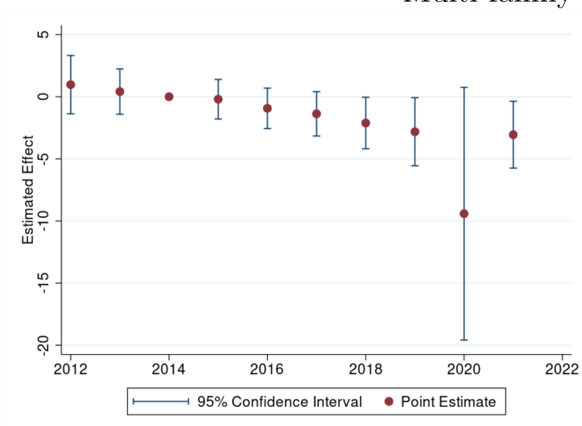


d) Wildfire Risk

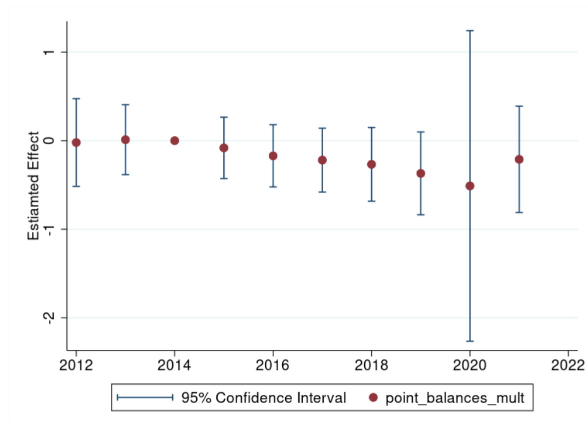
Figure 5: Multi-Family and Office Loans in Banks' Portfolios

This figure shows the results of estimating equation 1 with multi-famiily balances (in millions) in panels a) and b) and office loans balances in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Multi-family Loan Balances

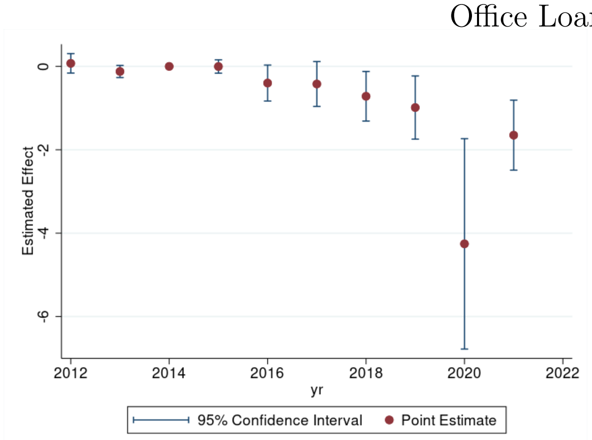


a) Flood Risk

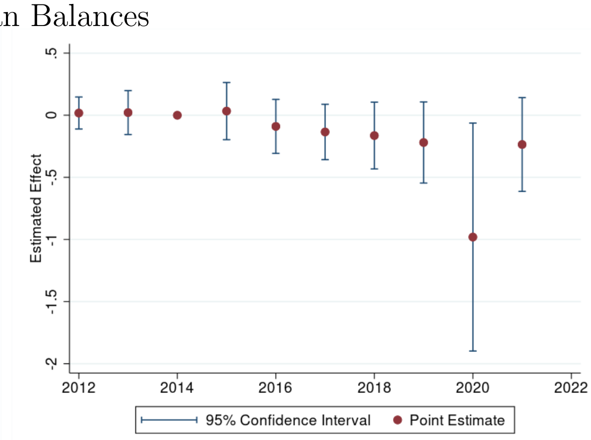


b) Wildfire Risk

Office Loan Balances



c) Flood Risk

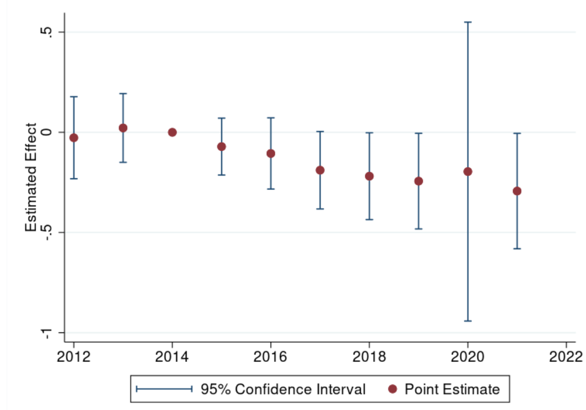


d) Wildfire Risk

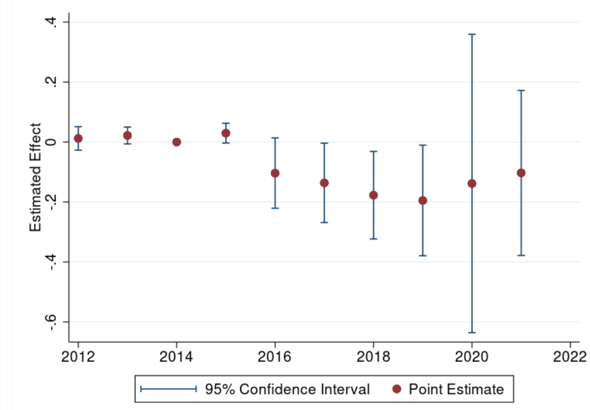
Figure 6: C&I Loans under $10 millions in Banks' Portfolios

This figure shows the results of estimating equation 1 with C&I loan balances of loans of $10 million or less (in millions) in panels a) and b) and with number of loans in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

C&I Loan Balances

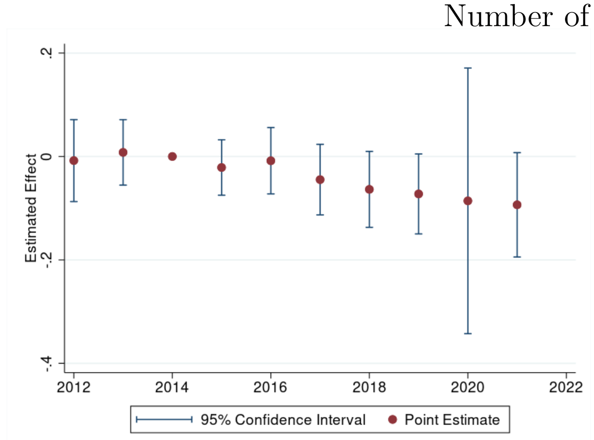


a) Flood Risk

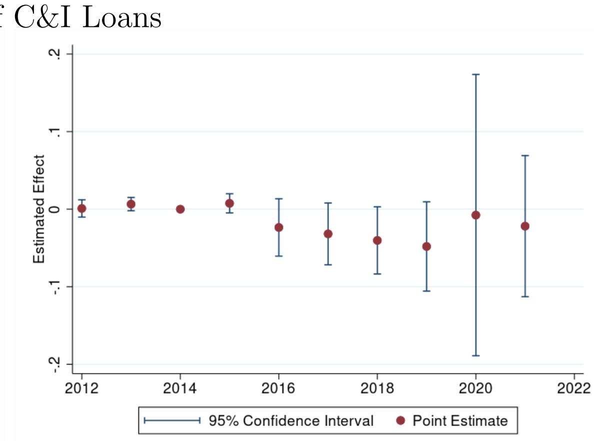


b) Wildfire Risk

Number of C&I Loans



c) Flood Risk

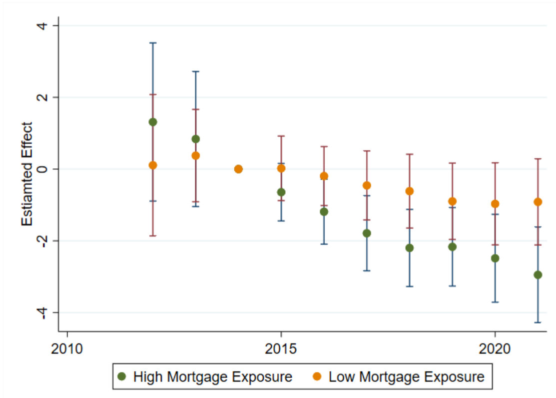


d) Wildfire Risk

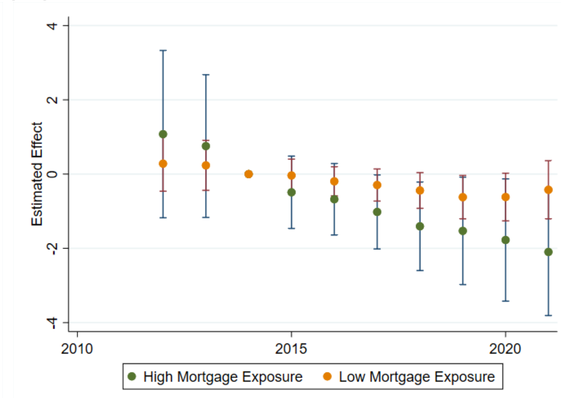
Figure 7: Number of Loans by Mortgage Exposure

This figure shows the results of estimating equation 1 with number of mortgages in panels a) and b) and with number of HELOCs in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. The samples are split at median mortgage share on bank holding companies balance sheets. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Mortgages



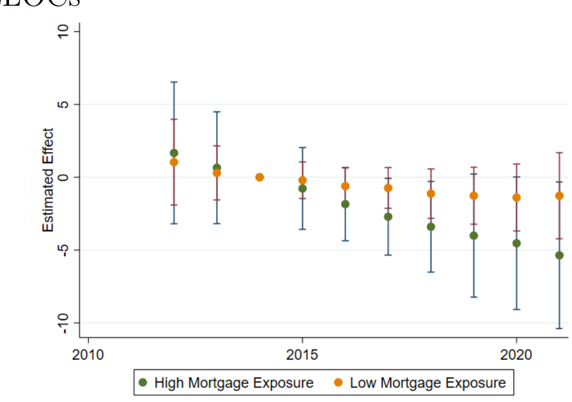
a) Flood Risk



b) Wildfire Risk

HELOCs

c) Flood Risk

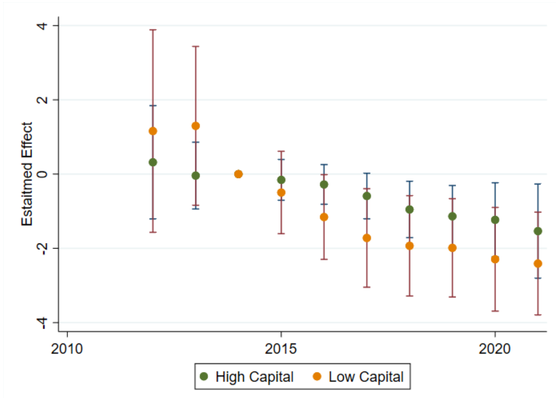


d) Wildfire Risk

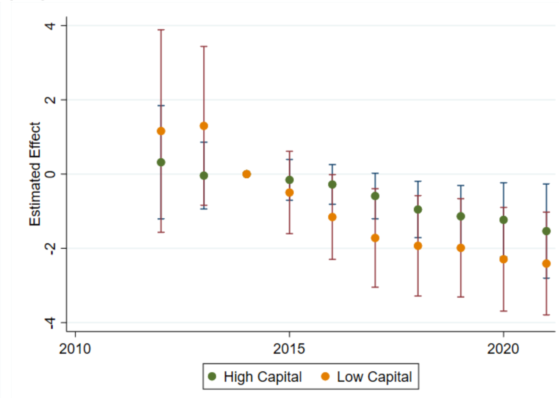
Figure 8: Number of Loans by Bank Capital

This figure shows the results of estimating equation 1 with number of mortgages in panels a) and b) and with number of HELOCs in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. The samples are split at median total leverage on bank holding companies balance sheets. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Mortgages

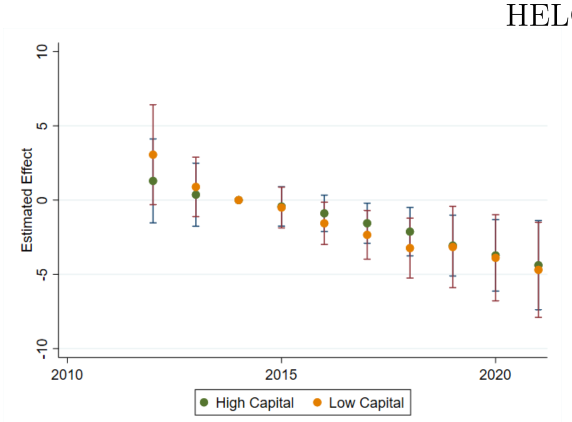


a) Flood Risk

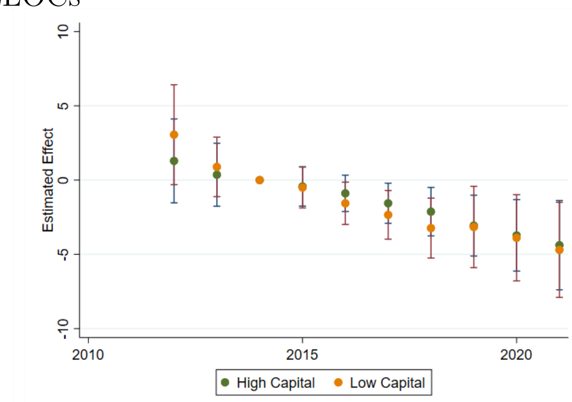


b) Wildfire Risk

HELOCs



c) Flood Risk

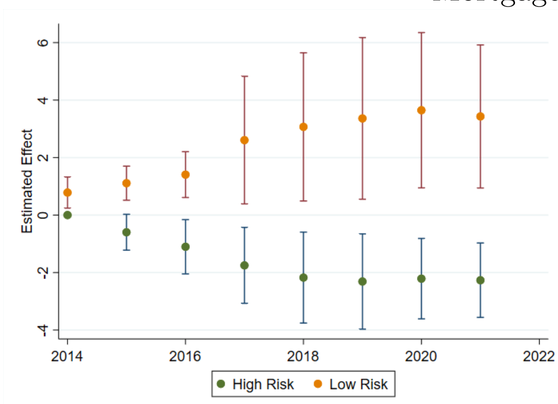


d) Wildfire Risk

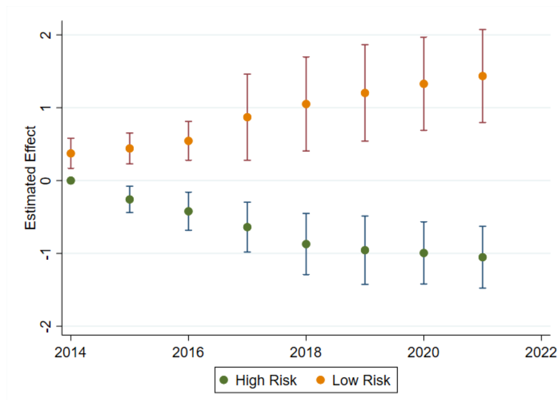
Figure 9: Mortgage Balances and Number of Loans by Borrower Risk

This figure shows the results of estimating equation 1 with mortgage balance by credit score group in panels a) and b) and with number of mortgages by credit score group in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. Low credit risk refers to the highest quartile of the credit score distirbution and high risk to lowest quartile. The second quartile is the base. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Mortgages Balances

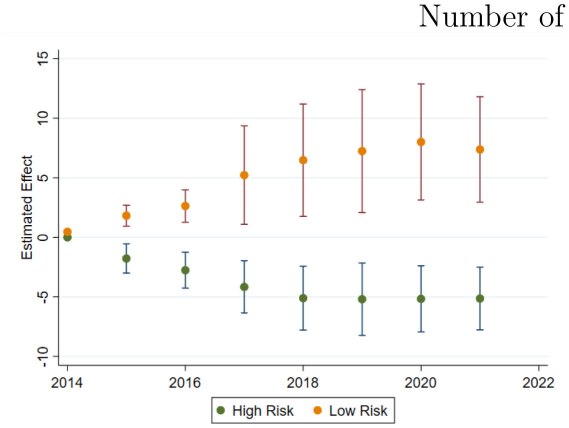


a) Flood Risk

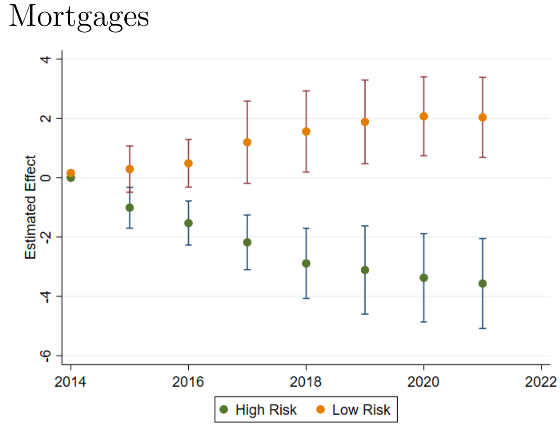


b) Wildfire Risk

Number of Mortgages



c) Flood Risk

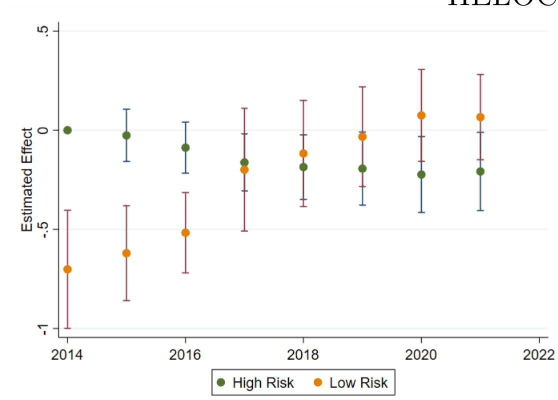


d) Wildfire Risk

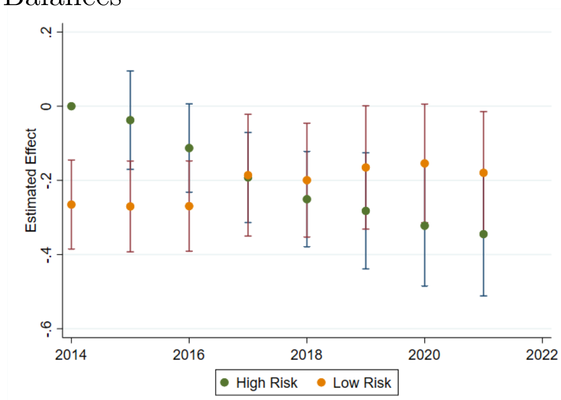
Figure 10: HELOC Balances and Number of Loans by Borrower Risk

This figure shows the results of estimating equation 1 with HELOCs balancese by credit score group in panels a) and b) and with number of HELOCs by credit score group in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. Low credit risk refers to the highest quartile of the credit score distirbution and high risk to lowest quartile. The second quartile is the base. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

HELOC Balances

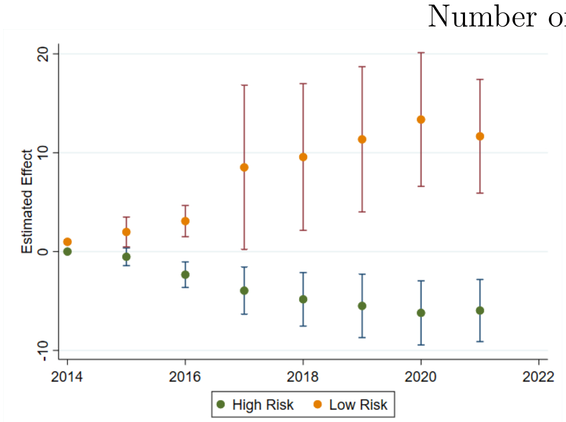


a) Flood Risk

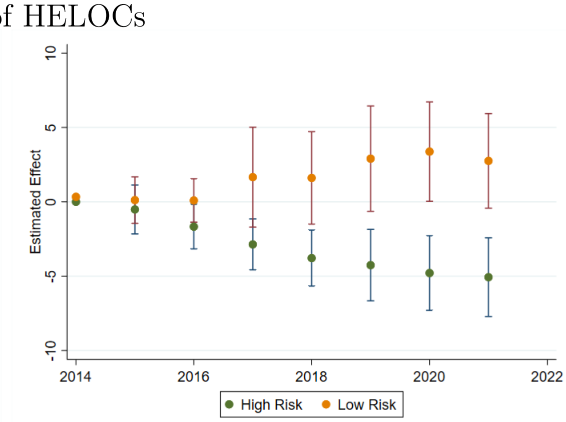


b) Wildfire Risk

Number of HELOCs



c) Flood Risk



d) Wildfire Risk

A Robustness Tests

Figure A1: Google Trends: Climate Change

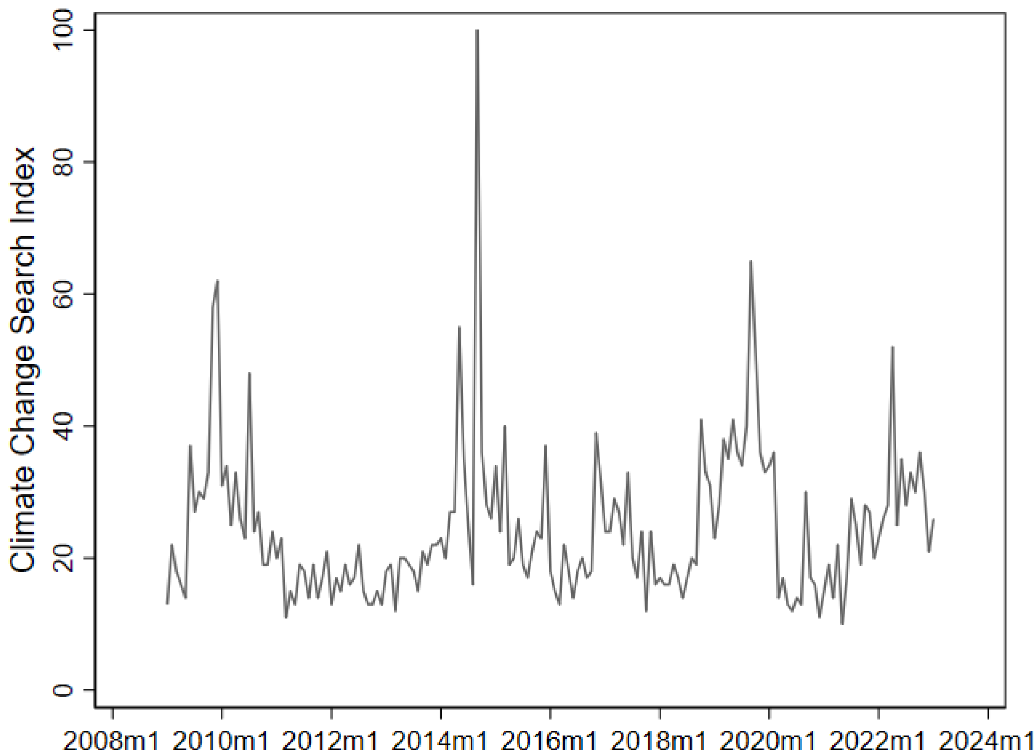
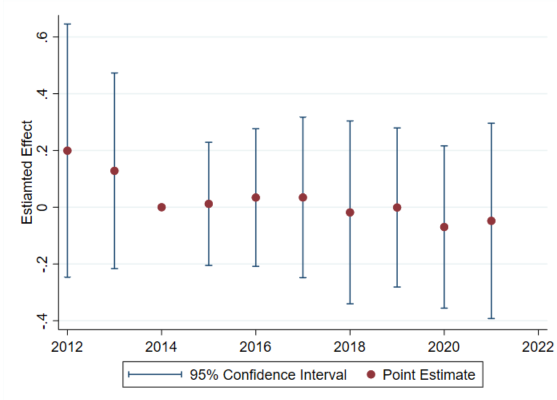


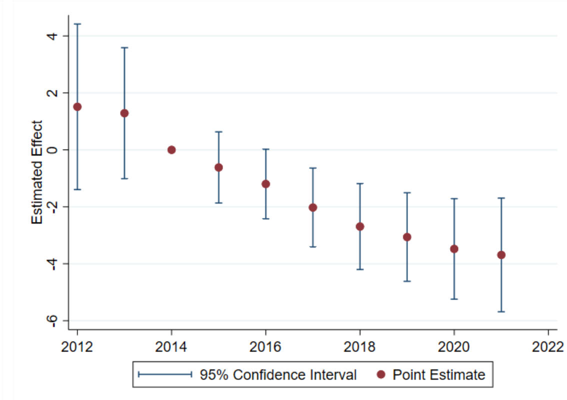
Figure A2: River Flood Risk

This figure shows the results of estimating equation 1 with mortgage balances (in millions) in panels a), number of mortgaes in panel b), HELOC balances in panel c) and number of HELCOs in panel d) as dependent variables. The climate risk measure is river flood risk. All counties with coastal flood risk are excluded. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Mortgages

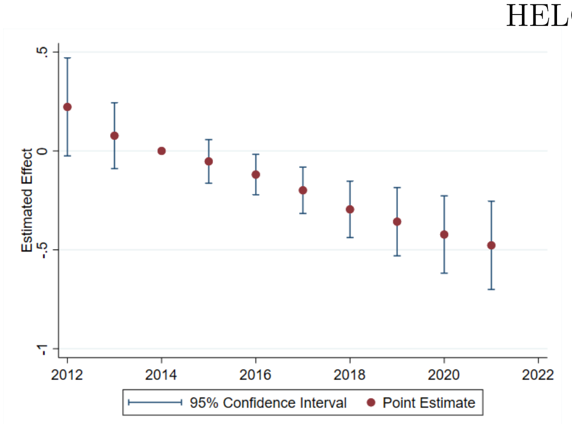


a) Balances

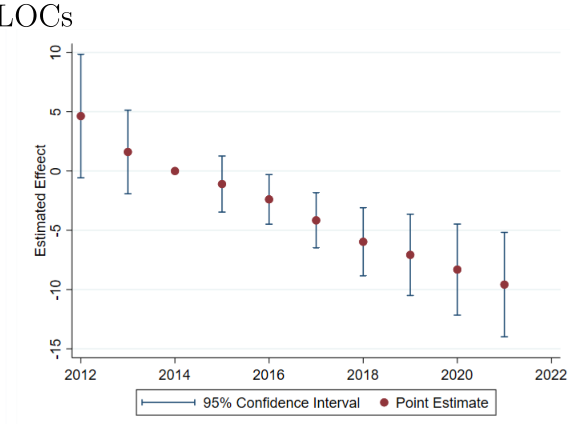


b) Number of Loans

HELOCs



a) Balances

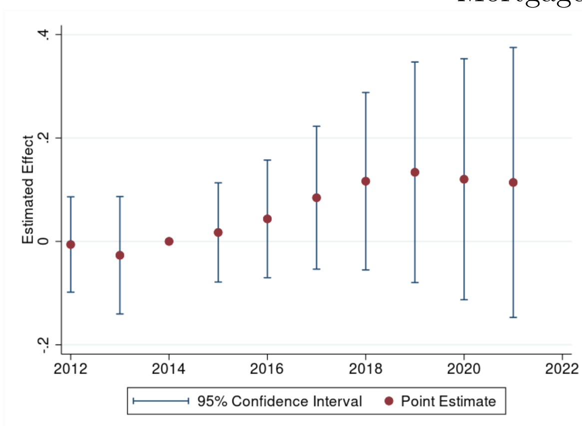


b) Number of Loans

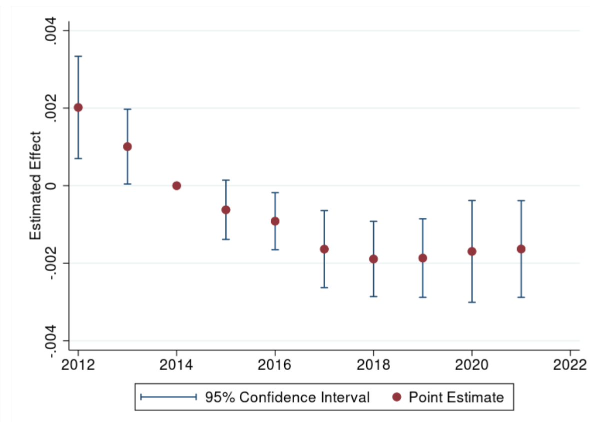
Figure A3: HELOC - County Exposure Split (Flood Risk)

This figure shows the results of estimating equation 1 with HELOC balances (in millions) in panels a) and b) and with number of loans in panels c) and d) as dependent variables. Large balance-counties are counties in the 75th percentile of the mortgage balance distribution. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Mortgages Balances

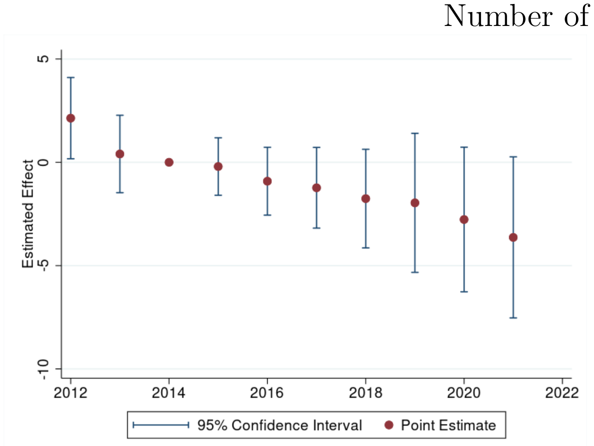


a) Large Balances

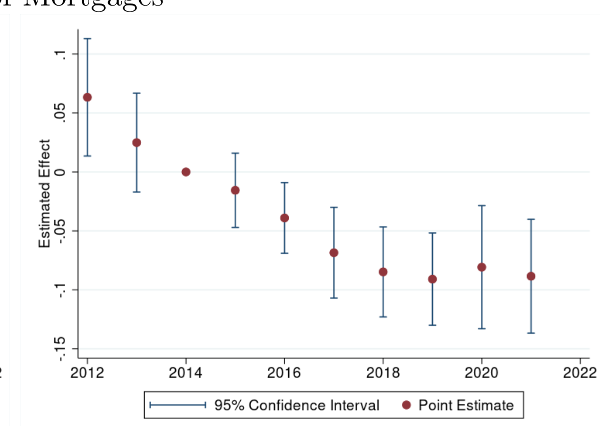


b) Small Balances

Number of Mortgages



c) Large Balances

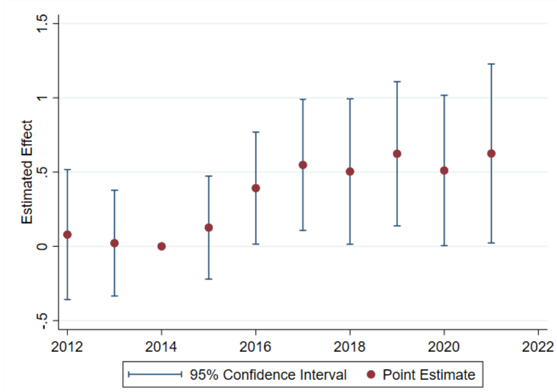


d) Small Balances

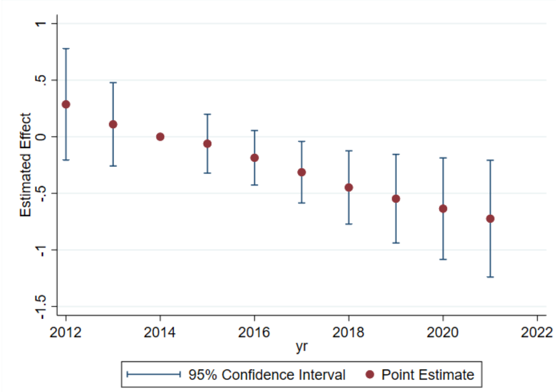
Figure A4: Wildfire Risk incl. California

This figure shows the results of estimating equation 1 with mortgage balances (in millions) in panels a), number of mortgaes in panel b), HELOC balances in panel c) and number of HELCOs in panel d) as dependent variables. The climate risk measure is wildfire risk and the regressions include California. All counties with coastal flood risk are excluded. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Loan Balances

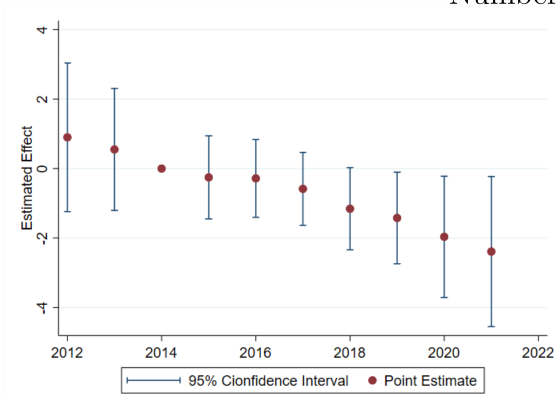


a) Mortgages

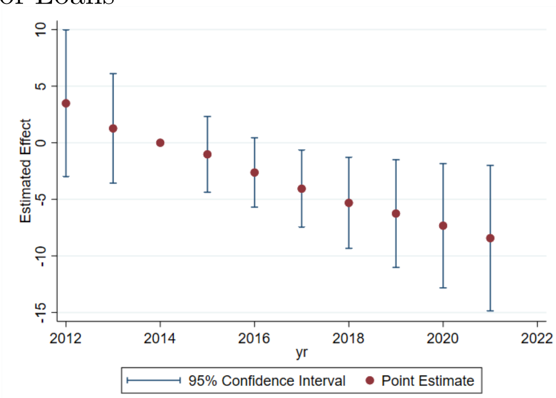


b) HELOCs

Number of Loans



c) Mortgages

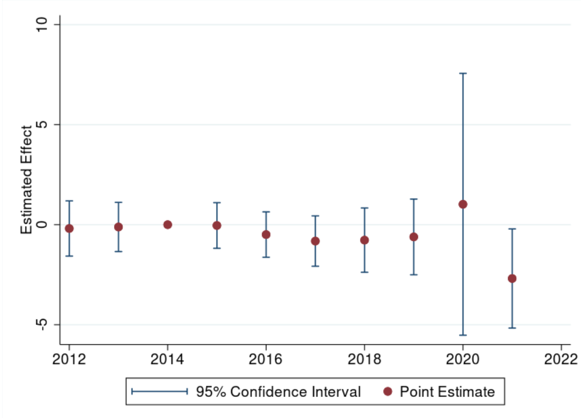


d) HELOCs

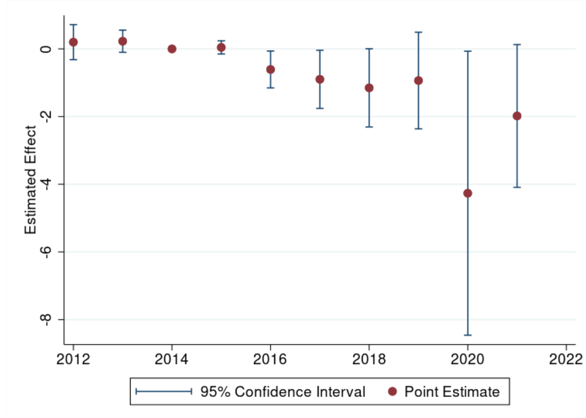
Figure A5: Commercial and Industrial Loans in Banks' Portfolios

This figure shows the results of estimating equation 1 with C&I loan balances of loans in panels a) and b) and with number of loans in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

C&I Loan Balances

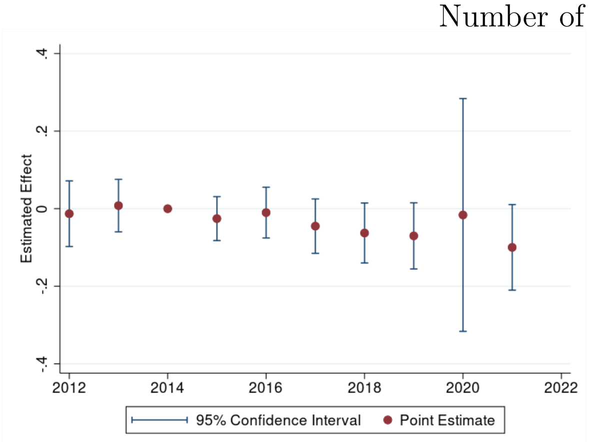


a) Flood Risk

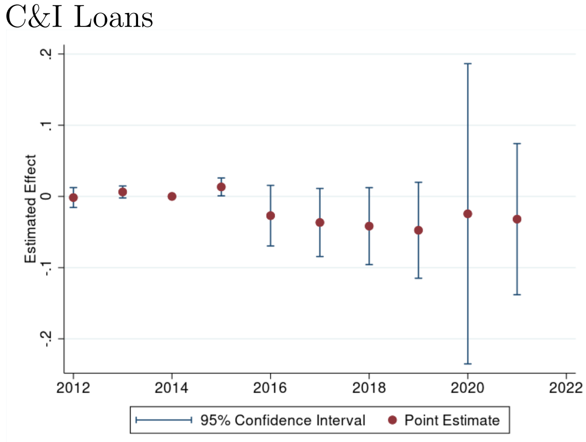


b) Wildfire Risk

Number of C&I Loans



c) Flood Risk

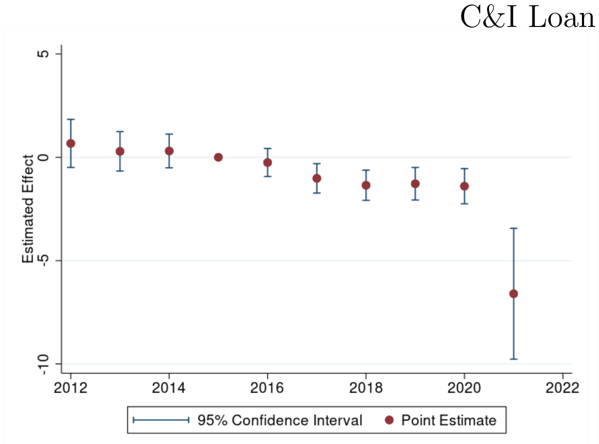


d) Wildfire Risk

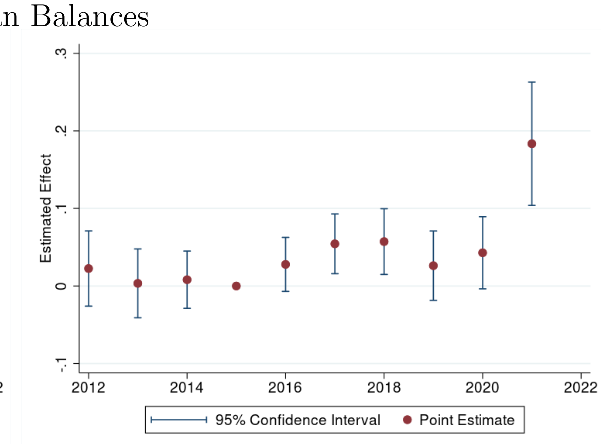
Figure A6: C&I Loans under $10 millions in Banks' Portfolios - Split by County Balances (Flood Risk)

This figure shows the results of estimating equation 1 with C&I loan balances of loans of $10 million or less (in millions) in panels a) and b) and with number of loans in panels c) and d) as dependent variables. Large balance-counties are counties in the 75th percentile of the mortgage balance distribution. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

C&I Loan Balances

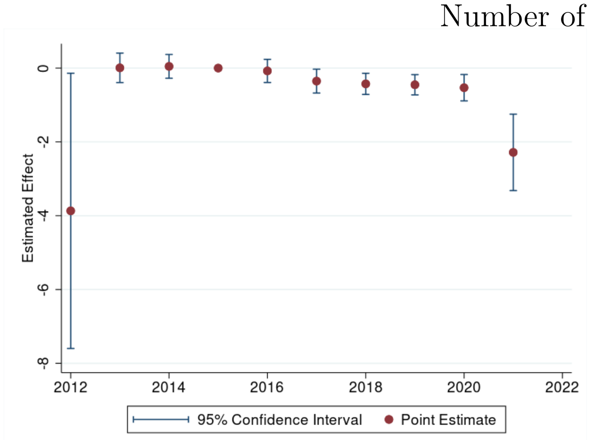


c) Large Balances

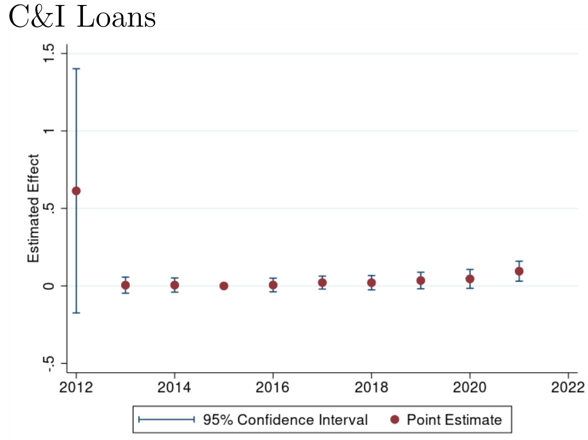


d) Small Balances

Number of C&I Loans



c) Large Balances

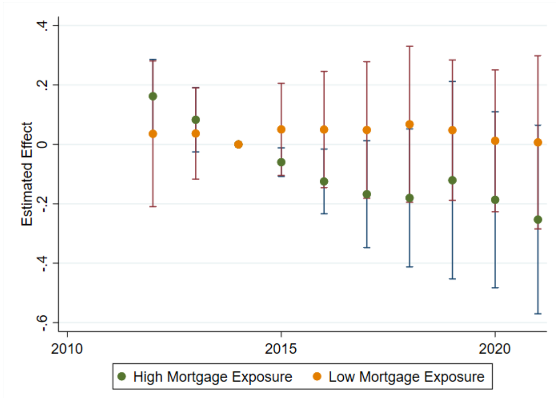


d) Small Balances

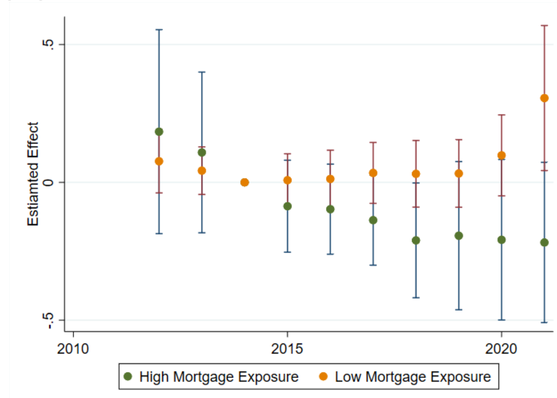
Figure A7: Loan Balances by Mortgage Exposure

This figure shows the results of estimating equation 1 with mortgages balances in panels a) and b) and with HELOCs balances in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. The samples are split at median mortgage share on bank holding companies balance sheets. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Mortgages



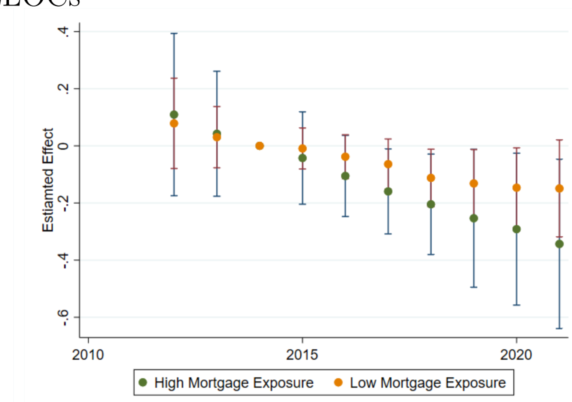
a) Flood Risk



b) Wildfire Risk

HELOCs

c) Flood Risk

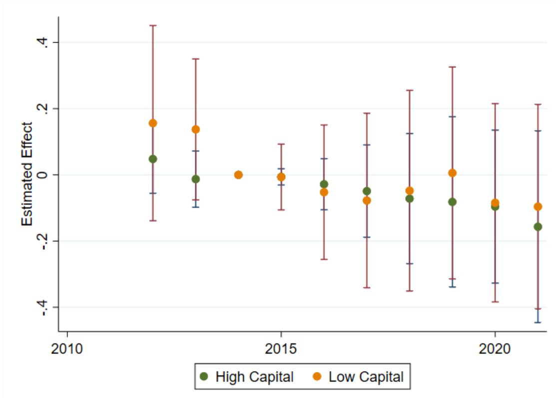


d) Wildfire Risk

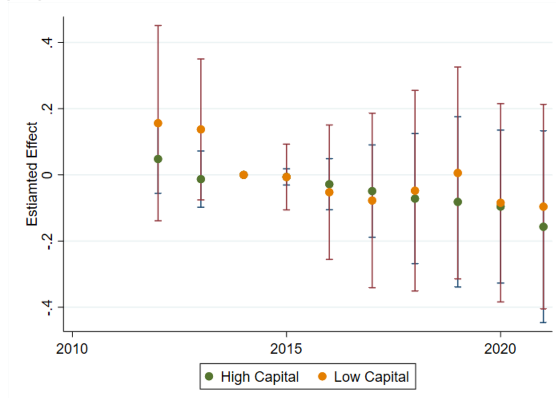
Figure A8: Loan Balances by Bank Capital

This figure shows the results of estimating equation 1 with mortgages balances in panels a) and b) and HELOCs balances in panels c) and d) as dependent variables. Panels b) and d) exclude counties in California. The samples are split at median total leverage on bank holding companies balance sheets. The regressions include total county-level wages (BLS), bank-county fixed effects, and bank time fixed effects. The standard errors are double-clustered at the bank-county and bank-year level.

Mortgages

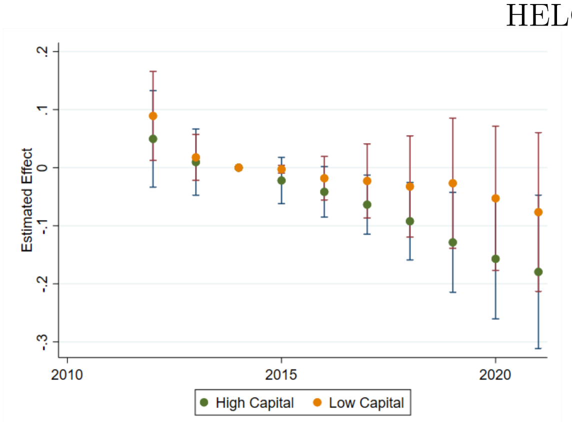


a) Flood Risk

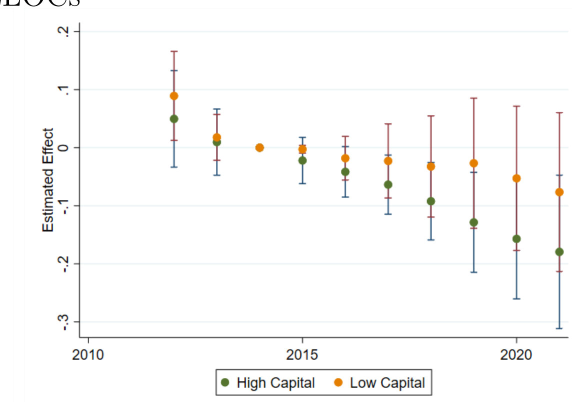


b) Wildfire Risk

HELOCs



c) Flood Risk



d) Wildfire Risk