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ADAPTATION USING FINANCIAL MARKETS: CLIMATE RISK DIVERSIFICATION THROUGH SECURITIZATION

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ABSTRACT

In the face of rising climate risk, financial institutions may adapt by transferring such risk to securitizers that have the skill and expertise to build diversified pools, such as Mortgage-Backed Securities. In diversified pools, exposure to climate risk may have a small impact on performance metrics such as deal losses, yield-to-maturity, and total returns, depending on the degree of spatial correlation and concentration. This paper builds a data set of the securitization chain from mortgage-level to MBS deal-level cash flows. Wildfires lead to higher rates of prepayment and foreclosure at the mortgage level, and larger losses during foreclosure sales. At the MBS deal level, a lower spatial concentration of dollar balances (lower spatial dollar Herfindahl), a lower spatial correlation in wildfire events (within-deal correlation), leads to a lower exposure to wildfire events. These quantifiable metrics of diversification identify those existing deals whose design makes them resilient to climate change. This paper builds optimal deals by finding the portfolio weights in a mean-variance framework that trades off return and risk. Extrapolating wildfire risk using a wildfire probability model and temperature projections in 2050, the paper provides and implements a portfolio diversification algorithm that builds climate-resilient MBSs whose returns are minimally impacted by wildfire risk even as they supply mortgage credit to wildfire prone areas.

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1 Introduction

Financial institutions face a range of physical and transition risks linked to climate change in their portfolios. In particular, the $13 trillion mortgage finance industry faces new location-based natural disaster risks as climate change increases risks from extreme heat, drought, extreme rainfall, sea level rise and hurricane storm surges. Some areas face more wildfire risks while others face more flood risk. A growing new literature estimates the impact of natural disasters such as wildfires and hurricanes on cash flows and prices.[1] An emerging literature assesses whether local disaster risk could lead to a new, aggregate, systemic risk factor (Jung, Engle & Berner 2021). Yet, whether these place-based risks pose aggregate risks remains an empirical question both in a portfolio context, and in a macroeconomic sense.

In credit markets, lenders have several adaptation strategies. First, they can retreat from areas they deem to be increasingly risky (Álvarez-Román, Mayordomo, Vergara-Alert & Vives 2024, Kim, Olson & Phan 2023). Second, they can demand that borrowers hold sufficient insurance to cover the remaining balance of the loan.[2] Third, they can charge higher interest rates and structure mortgage amortization to reflect risk-offsetting investments made by the home owner (Nguyen, Ongena, Qi & Sila 2022, Sastry 2022, Bakkensen, Phan & Wong 2023). Fourth, they can securitize the loans (Keys, Seru & Vig 2012, Hurst, Keys, Seru & Vavra 2016, Fuster, Lucca & Vickery 2022).

Recent research (Ouazad & Kahn 2022, Nguyen et al. 2022, Sastry 2022, Ouazad & Kahn 2023, Bakkensen et al. 2023, Baranyai 2025) has explored the behavior of major lenders before and after major disasters and has documented evidence that lenders move such loans off of their balance sheet. One potential interpretation of this finding is that this represents adverse selection.

An alternative hypothesis for why lenders who make loans in areas experiencing disaster risks increase their securitization rates is due to comparative advantage and gains to trade. The buyers of the loans (the securitizers) may have an edge in bundling spatially dispersed loans to create high return/low risk assets. Given the potential benefits of such financial technology, whether the cash flows of individual mortgages have significant impacts on mortgage portfolios and, ultimately, on financial institutions' balance sheets is an empirical question.

In this paper, we study every step in the securitization chain as we explore whether mortgage securitization facilitates natural disaster risk adaptation. From mortgage-level performance to pools and deals' cash flows at monthly frequency, this paper's data sheds light on the pooling of risk along the securitization chain.

First, the paper establishes key facts on the impact of wildfires on mortgage performance, using

[1] See Gallagher & Hartley (2017), Kousky, Palim & Pan (2020), Issler, Stanton, Vergara-Alert & Wallace (2020), Holtermans, Kahn & Kok (2023), Biswas, Hossain & Zink (2023), Ho, Huynh, Jacho-Chávez & Vallée (2023), An, Gabriel & Tzur-Ilan (2023), Addoum, Eichholtz, Steiner & Yönder (2023).

[2] For a discussion of flood insurance take up, see Kousky et al. (2020). For a discussion of frictions in flood insurance pricing, see Sen & Tenekedjieva (2021). For a discussion of insurers' withdrawal, see Sastry, Sen & Tenekedjieva (2023). For the unintended consequences of mandatory flood insurance, see Blickle & Santos (2022).

mortgage-level and monthly data on principal and interest payments, prepayments and foreclosures, as well as recorded losses.

Second, moving from mortgage-level econometric specifications to deal-level specifications, the paper estimates the potential impact of multiple correlated wildfires on the cash flows of MBS deals. Such impact crucially depends on quantifiable metrics of spatial diversification: (1) the within MBS-deal spatial correlation, i.e. the probability that wildfires occur in different geographic parts of the MBS deal; (2) a dollar Herfindahl index of the spatial concentration of dollars; (3) the number of 5-digit ZIP codes of the deal and the size of the deal. MBS deals are very heterogeneous in their levels of spatial correlation and concentration, giving us an opportunity to estimate the variety of impacts of wildfires on deals depending on their structure.

Third, the paper builds MBS deals with a given exposure to wildfire risk by choosing the spatial distribution of origination dollars across locations with heterogeneous yield-to-maturity and total returns. The ZIP-level cash flows are built using the cash flow accounting of Chernov, Dunn & Longstaff (2018) and Boyarchenko, Fuster & Lucca (2019) to capture interest rate risk, and the paper adds spatially correlated wildfire shocks that cause prepayments and defaults over and above those caused by interest rate movements and baseline local heterogeneity in hazard rates. The paper provides portfolios that maximize a regularized Markowitz (1952) mean-variance optimization program of the dimension of the number of 5-digit ZIP codes, with positive portfolio weights. Two salient empirical features emerge. First, the mean-variance maximizing deal features non-zero and economically significant exposure to wildfire risk as locations exposed to substantial wildfire probabilities may also exhibit lower baseline prepayment and foreclosure rates. Second, the mean-variance maximizing portfolio's yield-to-maturity and total returns when climate risk increases, as we detail below.

The paper focuses on the Private-Label Residential Mortgage Backed Securities (RMBS) market, studying \$1.7 trillions of originations and more than 300,000 mortgages. The benefit of the private-label RMBS data is that, since reforms of the market in the aftermath of the great financial crisis (Levitin, Pavlov & Wachter 2012), data transparency allows researchers and investors alike to observe the 5-digit ZIP code location of the real estate collateral of those mortgage loans. This provides an extensive *laboratory of natural experiments,* where we can trace out the impact of natural disasters on cash flows and prices. By observing the variety of pooling structures across sponsors, we can test whether more or less diversified deal respond less or more to shocks to parts of each deal.

Estimating the impact of wildfires on mortgage performance requires a control group with similar wildfire probabilities. Building such a propensity score requires estimating a time-varying in-sample probability of a wildfire, at the 5-digit ZIP code. We choose the 5-digit ZIP code as it is the geographic unit used in the majority of MBS prospectuses.[3] This paper builds a local wildfire

[3]Our extraction of the full-text of MBS prospectuses suggests the presence of keywords such as wildfire and natural disaster risk. Prospectuses also display measures of ex-post natural disaster risk exposure, see Section 4.2.

propensity score that statistically predicts the occurrence of wildfires at monthly frequency. The wildfire propensity score is built using pre-sample local average temperatures, in-sample local abnormal temperatures (PRISM Climate Group, Oregon State University 2004), local drought indices of the US Department of Agriculture (Svoboda, LeComte, Hayes, Heim, Gleason, Angel, Rippey, Tinker, Palecki, Stooksbury et al. 2002), USGS land cover data (U.S. Geological Survey 2021) to identify forested and developed areas at the Urban Wildland Interface (Radeloff, Helmers, Kramer, Mockrin, Alexandre, Bar-Massada, Butsic, Hawbaker, Martinuzzi, Syphard et al. 2018), electric grid infrastructure, and the road network (U.S. Census Bureau 2010).[4]

The impact of wildfires on mortgage performance is estimated by constructing a longitudinal panel of control and treatment mortgages with similar wildfire propensities, and by conditioning on the evolution of local amenities. As such, by controlling for local $\times$ year-month fixed effects, and by controlling for mortgage fixed effects, the identification compares the change in the mortgage performance in mortgages in 5-digit ZIP codes affected by wildfires vs those not affected by wildfires, within the same county in the same year-month, and weighted by the ZIP-level Wildfire Propensity Score. Double-clustered standard errors by mortgage and year-month suggest significant impacts on the probability of prepayment and foreclosure in the immediate months following the event, and lasting for at least 12 months following the event. This effect is consistent across both California and other U.S. states. Evidence suggests that a smaller share of the unpaid principal balance is recovered in case of a foreclosure caused by a wildfire vs. a foreclosure caused by other types of events.

We then move from the individual mortgage-level analysis to the MBS deal-level analysis. The impact of wildfires on MBS deals is identified by focusing on events where more than 5%, 10%, or 15% of the unpaid principal balance of a deal is affected. The frequency of these events has increased over time. The econometric specification focuses on a -9 months to $+36$ months time window around each such event, and controls for deal and year-month fixed effects. MBS deals with more than 10% or 15% of their unpaid principal balance in locations affected by wildfires tend to experience strictly positive cumulative losses in the months following a wildfire. Overall, the impact of a wildfire on a deal intensifies monotonically as the share of a deal that is affected increases and the time following a wildfire extends.

An MBS' propensity to be hit by a wildfire is the average, across the geographic locations of the MBS, of the Wildfire Propensity Score, weighted by the dollars of unpaid principal balance. The MBS Propensity Score is a good predictor of the *average* propensity of a dollar of unpaid principal balance to be affected by a wildfire. Yet, this average remains typically low. Empirically significant events occur when an MBS experiences a *tail event*: when wildfires occur at the same time in different locations, and when dollar originations are concentrated in a few locations. An MBS deal may also be repeatedly exposed over multiple months, hence the total variance depends

[4]These covariates represent different dimensions of adaptation. See Bayham, Yoder, Champ & Calkin (2022) for an analysis of the dynamic incentives to mitigate and respond to fires.

on the autocorrelation, i.e. probability of repeated hits.

To measure the propensity for tail events, we decompose the variance of an MBS deal's wildfire exposure into three terms: (1) a *spatial correlation term*, which does not vanish as the number of mortgages in the pool increases; pooling mortgages with correlated risks does not lower the variance of wildfire risk. (2) a *Herfindahl term* of the concentration of dollar originations across ZIPs, which measures how evenly (low Herfindahl) or unevenly (high Herfindahl) distributed these dollar originations are. These two metrics are in addition to deal size and the number of ZIPs in a deal.[5]

Econometric analysis suggests indeed that MBS deals with a high spatial correlation, a high spatial Herfindahl index, a lower number of 5-digit ZIP codes are more likely to see a large share of their unpaid principal balance exposed to wildfires in a given month. Larger originators tend to have a greater ability to diversify spatial risk. For them the within deal spatial correlation is close to the nationwide spatial correlation.

These results suggest a blueprint for MBS sponsors that wish to design MBS deals that have a given exposure to wildfire risks. This problem is akin to building a portfolio of assets, and the results of the Markowitz (1952) optimization at the 5-digit ZIP code level can be explained by running a Koijen & Yogo (2019) asset demand system estimation on the optimized weights. In such an approach, the share of dollars originated in each 5-digit ZIP codes is determined by a McFadden (1974) probabilistic model where the share is pinned down by the Wildfire Propensity Score, and a vector of covariates including household income, FICO score, and other borrower and mortgage characteristics.[6]

While the specific choice of the portfolio depends on the preferences of the investor, mean-variance optimization exercises run in this paper over more than a 1,000 ZIP codes across the Western states suggest that investors face a trade-off in a number of locations: areas exposed to wildfires may have lower baseline hazard rates and higher interest rates. The mean-variance-maximizing portfolio has a non-trivial exposure to wildfire-prone areas. As temperatures increase, an important take-away is that while mean-variance-maximizing deals reduce their origination volume in wildfire-exposed areas, the initial optimal deal is *already* resilient to rising climate risk.

This paper contributes to at least four distinct literatures. First, this paper adds to the literature documenting the benefits of securitization. This paper's mechanics suggest an additional value-added of mortgage securitization, in addition to the other benefits in terms of regulatory arbitrage and liquidity (Loutskina & Strahan 2009, Loutskina 2011, Gete & Reher 2021, Fuster & Vickery

[5] We also acknowledge the role of (3) the time series autocorrelation of wildfire events plays a role when assessing the variance over time spans of multiple months.

[6] Credit supply can affect the volume and type of mortgages and the corresponding collateral. Credit supply affects real estate prices (Favara & Imbs 2015, Ouazad & Rancière 2019, Adelino, Schoar & Severino 2025). Credit supply also affects the interest rate as supply shocks affect the equilibria in local credit markets. The model can be extended to allow for a supply elasticity. This would be akin to estimating the demand (by MBS sponsors) and the supply of mortgages (by lenders) as in Berry, Levinsohn & Pakes (1995).

2015). As the majority of mortgages are originated and distributed, the securitization technology provides a specific spatial diversification "value-added" that enhances the risk profile of MBSs, and the paper quantifies such benefit. These benefits extend to other vehicles such as Insurance-Linked Securities. Such securitization technology, when guided by the tools described in this paper (spatial correlation, Herfindahl of dollar originations, size of deal, number of ZIPs, and autocorrelation of risk), provides cash flows with lower variance compared a single undiversified 100 dollar notional. The paper's simulated MBSs also show that more spatially diversified MBSs exhibit higher prices, thus highlighting the importance of the pricing of risk in MBSs, in addition to the pricing of risk at the mortgage-level before securitization (McGowan & Nguyen 2023).

Second, the takeaways of this paper should be relevant for a broad range of financial participants developing tools to adapt to climate risk. The paper contributes to the literature by observing the time-varying contents of deals and pools, bringing an explicit empirical validation for the tools built with individual asset-level data only (Li & Su 2024). This paper accounts for microeconomic spatial risk at both the mortgage and deal levels over and above the macroeconomic risk factors documented in Chernov et al. (2018). The take-aways of this paper should be relevant for financial participants optimizing the pooling of cash flows of Insurance Linked Securities (ILSs), and of Credit Risk Transfers (CRTs).[7] The results of this paper are also relevant for the spatial diversification of asset portfolios, such as those of insurers (Jung et al. 2021, Jung, Engle, Ge & Zeng 2024). Davidson & Levin (2014) suggests that the spatial diversification of pools is an important metric when dealing with unemployment rates, fluctuations in household income, and changes in household structure triggering mobility and thus prepayment. The current paper provides an analytical framework to design MBS pools using a quadratic problem of risk-return optimization, and summarizes the results of this analysis using asset demand systems. An important contribution to the development of climate-risk hedged portfolios is Alekseev, Giglio, Maingi, Selgrad & Stroebel (2022). Mortgage-Backed Securities differ from mutual funds in that they are not actively managed, and the mortgages in the pool amortize over time. The cash flows of fixed income assets such as mortgages are inherently left skewed and leptokurtic, suggesting that the role of spatial correlations may be more important in Mortgage-Backed Securities than in mutual funds.

Third, this paper contributes to the literature on the impact of climate change at the aggregate level (Kahn, Mohaddes, Ng, Pesaran, Raissi & Yang 2021), here focusing on tying security-level performance (cash flow, yield-to-maturity and total return) to portfolio-level outcomes. An extensive literature estimates the impact of climate risk on balance sheets (Acharya, Berner, Engle, Jung, Stroebel, Zeng & Zhao 2023), and this paper suggests that portfolio rebalancing and securitization may be an important margin of adaptation when climate risk increases.[8] This paper also focuses on expanding the set of possible securities rather than taking the span of securities as given. This set of securities may expand and adapt as wildfire-prone areas of our sample experience statistically

[7] Gete, Tsouderou & Wachter (2020) estimates the impact of hurricanes on CRT yields.

[8] See also Heipertz, Ouazad & Rancière (2019).

significant local temperature increases and increases in the drought index. This paper collects temperature data from 29 models of the Coupled Model Intercomparison Project Phase 6 (CMIP6). These models were part of the 6th assessment report of the Intergovernmental Panel on Climate Change. We use such forecasts to predict local wildfire probabilities using the coefficients of our wildfire propensity score model. Temperature is a key driver of wildfire propensity scores. This paper provides financial adaptation tools to change the design of MBSs to adapt to the forward-looking challenge of global warming. In highlighting the benefits of pooling cash flows across locations with heterogeneous risk levels, this paper is the financial counterpart to an important literature in international trade highlighting the impact of rising correlations (Dingel, Meng & Hsiang 2019). In the world of Mortgage-Backed Securities with no Krugman (1991) iceberg cost, the pooling of risk provides significant diversification benefits.

Fourth, this paper is complementary to the literature suggesting that natural disaster risk leads to more skin in the game for borrowers. One of the possible adaptation responses of financial institutions at the mortgage level is to require a higher downpayment and more equity (Sastry 2022) for new mortgage originations. We observe both a decline of the LTV in the aftermath of wildfires, as well as the quantification of the benefits of securitization. Equity is likely to reduce moral hazard, which alleviates concerns about informational equilibria that prevent risk pooling. Equity is thus likely a *complement* rather than a *substitute* to pooling for the securitization of cash flows. Wagner (2022) quantifies adverse selection in insurance markets for natural disasters. Such estimates could be a predictor of the extent of possible securitization.

This paper should be useful to policymakers and practitioners. For policymakers, this paper suggests that the benefits of the securitization technology may lead to more valuable securities. Further work may reveal that a significant share of agency MBSs are well-diversified across the nation, as they report a breakdown of dollar originations across a significant number of states. One potential approach to studying Agency MBSs would be to study the spread between To Be Announced (TBA) transactions (Vickery & Wright 2013), where the contents of the pool cannot be observed by the investor, and Specified Pool (SP) transactions; analysis of such spread was performed by Fusari, Li, Liu & Song (2022) in a different context. The correlation between such spread and major events such as Hurricanes Katrina, Sandy, and Harvey may be a fruitful area for research.

This paper's implications for the pooling of cash flows may help in the design of Credit Risk Transfers (Gete, Tsouderou & Wachter 2024), which transfer credit risk traditionally held by the Government Sponsored Enterprises back to private sector investors. For practitioners, this paper suggests a systematic portfolio-building approach specific to fixed income securities for the pooling of climate risk.

This paper is structured as follows. Section 2.1 presents the private-label RMBS data. Section 2.2 matches local temperature data from the PRISM Climate Group, local drought data from the US Department of Agriculture, as well as USGS and DoT data to build a wildfire propensity score. Section 3 estimates the impact of wildfire events on individual mortgage cash flows. Section 4 analyzes the structure of MBS deals, and derives the key spatial diversification metrics. It estimates the impact of individual wildfire events on MBS deals' performance and balance. Section 5 then uses the results of Section 3 to build counterfactual deals with a set of targeted moments of yield to maturity and returns.

2 Data Sources: Cash Flows and Wildfire Risk Propensity

This paper builds data that allows us to track individual mortgage payment history, where the collateral is geolocated at the 5-digit ZIP code level, and matches these individual mortgages to their deal-level cash flows. To estimate the impact of *climate risk* on such performance, we also need data on local natural disaster risk probabilities and occurrence. Data will also be used when building synthetic Mortgage-Backed Securities in Section 5.

2.1 Data and Institutional Details: The Private-Label MBS Market

Information on private-label RMBS is obtained using three sources. First, we use mortgage origination data from *Corelogic's Non-Agency RMBS* data set. The Master file includes information about the creditworthiness of the applicant (FICO score), the characteristics of the mortgage (LTV, origination date, maturity, origination amount, closing balance, interest rate at closing, 5-digit ZIP Code of the house, state), and characteristics of the originator and servicer. The non-Agency RMBS origination records contain identifiers for the pool ID and the deal ID. This enables us to link a mortgage to its pool and deal.

Second, a series of monthly files with payment history for each month between March 1992 and February 2021, with a unique loan identifier for longitudinal analysis, the current balance, the current rate, the scheduled principal payment, the Mortgage Bankers' Association performance code (C=Current, 3=30 days delinquent, 6=60 days delinquent, 9=90 days delinquent, F=Foreclosure, R=Real Estate Owned, 0=Paid Off, X=Missing), and the loss amount, when appropriate. No losses occur until the loan is disposed of, when the balance goes to zero due to default and liquidation. Thus, the time at which the loss is recorded may be later than the time of default.

Third, the Option-Adjusted Spreads of MBS tranches were hand-collected using *Bloomberg Data Service (BDS)* API calls. Bloomberg IDs for the tranches were obtained using the Corelogic PLS RMBS crosswalk. These OAS measures are used when computing the prices and then total returns of simulated Mortgage-Backed Securities.

2.2 Wildfire Risk: Time-Varying Exposure and Correlations

Data on wildfire perimeters is available through multiple sources on geocoded perimeters and on the characteristic of the fires. For 2000–2019, we use GeoMAC records and perimeters. For 2014 onwards, we use Wildland Fire Interagency Geospatial Services (WFIGS) records and perimeters, for which an Integrated Reporting of Wildfire Information (IRWIN) ID is included.

We then estimate the average annual exposure of 5-digit ZIP codes to wildfires, weighted by surface area, housing units, or housing values. These weights are estimated using the American Community Survey. Surfaces are estimated using the US National Atlas projected Coordinate Reference System (EPSG 9311).

Figure 3 displays the US-wide monthly surface area, housing units, and housing value exposed to wildfires. We observe an increasing exposure, specifically when weighting by housing value and housing units.

[Figure 3 about here.]

The dollar-weighted spatial correlation in wildfire exposure across locations is rising as well from levels between 2 and 2.5% to levels between 8 and 12.5%, depending on the weighting method and the time window. Figure 4, panels (a), (c), (e), presents the spatial correlation across 5-digit ZIP codes in wildfire occurrence using an annual sliding time window between *t-2* and *t+2*. The spatial correlation is also presented at monthly frequency on panels (b), (d), (f), with a time window of 6 months (red line) and 12 months (blue line). A major factor in the rising spatial correlation is thus the rising value and volume of housing units in affected areas. When estimating the spatial correlation by surface area on panels (e) and (f), the increase in spatial correlation is less noticeable.

[Figure 4 about here.]

2.3 A ZIP-Level Wildfire Propensity Index

We build time-varying wildfire propensity measures (probabilities) that serve three purposes: (a) as a way to build control groups of mortgages and MBS deals with similar dollar weighted wildfire propensity scores, (b) as a way to relate global climate change projections to the ZIP-level probability of wildfires over time, (c) as a way to parameterize the spatial diversification of risk with Koijen & Yogo (2019) portfolio weights based on the wildfire propensity score.[9]

Our methodology centers on climate and geographical factors for estimating the probability of wildfires. To acquire historical records and perimeters, we utilize the National Interagency Fire Center's database of wildfires.[10] Our dataset comprises GeoMAC data for wildfires before 2014 and

[9] For alternative approaches at different levels of aggregation and with different techniques such as neural networks, see, e.g. Stanton, Wallace, Issler & Zhao (2025) and Biswas et al. (2023).

[10] For detailed datasets, please refer to https://data-nifc.opendata.arcgis.com/datasets/wildland-fire-incident-locations/about and https://data-nifc.opendata.arcgis.com/datasets/nifc::wfigs-interagency-fire-perimeters/about.

WFIGS data thereafter. These projects are complementary, with WFIGS continuing the GeoMAC database. The final wildfire dataset provides monthly observations at the ZIP-code level, including the area affected by each wildfire, obtained by merging with ZIP code maps. For geographical information and roads, we use US Census TIGER/Line Shapefiles.[11]

To predict wildfire propensities, we consider the share of developed and forest areas within a ZIP code, limiting our sample to ZIP codes with a non zero forest area. Data on developed and forested areas come from the National Land Cover Database, available at the ZIP-code level from 2001 to 2021. We calculate the share of developed and forested areas and merge these with ZIP code shapefiles. Additionally, we compute the length of (above-ground) electricity and road lines in a ZIP code, under the assumption that electricity lines could facilitate wildfires, while roads may impede their spread. Electricity lines data are obtained from Homeland Infrastructure Foundation-Level Data.[12]

Temperature data are sourced from PRISM Climate Data.[13] We employ two temperature measures: the mean of monthly temperatures in a ZIP code until 2000, i.e. before the start of the sample, used as a fixed mean temperature in regressions from 2001 onward, capturing the overall temperature characteristic; and abnormal temperature, defined as the deviation from the mean temperature in a ZIP code. Monthly drought index, another predictor for wildfires, are obtained from the US Department of Agriculture and matched with ZIP-code shapefiles to have monthly drought indices for each ZIP code.

After merging all datasets, we run the following logistic regression of the wildfire indicator which is equal to one if there is a wildfire in a ZIP code from 2001 to 2021:

$$\begin{aligned}\log\left(\frac{P(\text{Wildfire}_{it}=1)}{1-P(\text{Wildfire}_{it}=1)}\right) &= \beta_0+\beta_1\text{Pre-Sample Average Temperature}_i\\ &+\beta_2\text{Abnormal Temperature}_{it}+\beta_3\log(\text{Drought})_{it}\\ &+\beta_4\text{Forest Share}_{it}+\beta_5\text{Developed Share}_{it}\\ &+\beta_6\text{Electricity Lines}_{it}+\beta_7\text{Road Length}_{it}\\ &+\beta_8\log(\text{ZIP Code Area})_{it}+\text{Month}_t+\text{Location}_z+\epsilon_{i,t} \quad (1)\end{aligned}$$

where Month_t is a year-month fixed effect and Location_z is either a state or CBSA fixed effect.

Regression results are detailed in Table 2. All regressions except regression (1) incorporate state, year and month fixed effects. In regression (1), we do not use any fixed effects to increase the number of observation in the logistic regression. Instead of fixed effects, we use the number of past wildfires in the state of the collateral property to capture the impact of unobservable wildfire determinants.

[11] For more details, please visit https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html.

[12] For more details, please visit https://hifld-geoplatform.opendata.arcgis.com/datasets/geoplatform::transmission-lines/explore.

[13] For more details, please visit https://prism.oregonstate.edu/.

In regressions (1) to (3), time fixed effects capture unobservable monthly factors influencing wildfire likelihood, while location fixed effects account for time-invariant, local geographic factors. The natural logarithm of the ZIP code area, a significant contributor to wildfire probability, is controlled for in all regressions. Our main specification considers wildfires affecting over 10% of the ZIP code area, ensuring a clean control group. Alternative specifications using 5% and 15% thresholds are presented in the Online Appendix.

[Table 2 about here.]

Across all regressions, mean temperature, abnormal temperature, and drought index consistently increase the likelihood of wildfires. Forest share significantly increases wildfire probability applied alone or when interacted with drought in regressions (1), (3), and (4), indicating an increased wildfire probability with higher levels of drought. Regressions (1) and (4) introduces controls for developed share, electricity lines, and road length. Larger developed areas decrease wildfire probability significantly (1% level), while longer electricity lines increase it (10% level). Road length decreases wildfire probability in regression (1), potentially due to blocking the spread of wildfires. The number of state-level past wildfires also increase the wildfire probability in regression (1).

From each column of Table 2, we derive wildfire propensity scores (PS0 to PS3) to be used for deal-level analysis. Locations with no wildfires are dropped, and their probability is considered zero. Propensity scores also serve as weights in mortgage-level analysis, with PS3 from regression (3) specifically used.

Evolution of Wildfire Propensity Scores Over the Last Two Decades

An extensive attribution literature studies the potential causal link between anthropogenic climate change and the occurrence of local natural disasters. Here we illustrate the evolution of the key parameters of the Wildfire Propensity Score, temperature and drought, and their correlation with global temperatures as measured by the Global Mean Surface Temperature (GMST).

Figure E presents two maps of the average annual change in temperature at the 5-digit ZIP code level (upper panel) and the average annual change in the USDA drought index (lower panel). The temperature map suggests increases in temperature in southwest, the northwest, and the Atlantic coast, including Florida. Although parts of the coterminous US experience temperature declines, the average and median temperature increases are positive and statistically significant. Hypothesis tests using the standard errors of an OLS t-stat and using the standard errors of a quantile regression on the constant suggest statistically significant increases. The time period is 2000-2022 and the unit of analysis is the 5-digit ZIP code (ZCTA5). The average annual increase is +0.01 degree Celsius significant at 99%. The median increases by +0.04 per year, significant at 99%. Extremes experience larger changes: the 90th percentile of annual changes is +1.03 degree Celsius, significant at 99%. The lower end of the distribution experiences changes as well.

The lower panel of Appendix Figure E suggests that the wildfire-prone areas of the southwest and the northwest also experienced positive average annual changes in the drought index. In contrast, the southeast of the U.S., including Alabama, Mississippi and the Florida panhandle experienced declines in the drought index. It is interesting to notice that, consistent with the map of wildfire perimeters, southwest Florida experienced both a positive annual temperature and a positive increase in the drought index. This is correlated with the occurrence of wildfires reported in GeoMAC data.

3 The Impact of Wildfires on Individual Mortgage Cash Flows

After constructing a predictive model for wildfire propensities, our focus shifts to analyzing mortgage-level cash flows. We aim to explore how wildfires affect mortgage cash flows, specifically examining the likelihood of foreclosure, prepayment, and losses after foreclosure. To achieve this, we employ an event study design.

3.1 Mortgage-Level Data and Model Design

We source mortgage cash flow and characteristic information from CoreLogic. Our sample comprises mortgages securitized in non-agency MBS deals, allowing us to monitor the monthly performance, characteristics, and locations of individual mortgages. Given that our wildfire data are organized by ZIP codes, we merge this information with the monthly mortgage performance data for each ZIP code and month.

A mortgage is classified as foreclosed in a given month if it is labeled as "F" for foreclosure or "R" for REO in the delinquent history variable from CoreLogic. For prepayment, we classify a mortgage as prepaid in a month if the delinquent history indicator is "0," the loan is not foreclosed or in REO, and loan loss is zero.

For both foreclosure and prepayment, we create separate survival data designs. Mortgages enter our dataset upon origination or the beginning of our sample period (starting in 2001), whichever comes first. An exit from our dataset occurs when a mortgage matures, our sample period concludes (in 2021), foreclosure or REO status is reached, or prepayment occurs. In prepayment analysis, a loan exits the data if the loan is delinquent for three months. We exclude all observations from mortgages with a loss exceeding 120% after foreclosure or a loss reported when there is no foreclosure. Our analysis, which uses propensity scores as weights, excludes mortgages from states without wildfires, including Alaska.

In our event study design, the treated sample comprises mortgages exposed to wildfires. We include the nine months before the wildfire starts and the 12 months following. To avoid pre-trend or extended impact of previous wildfires, we cover wildfires that do not occur in two consecutive years, so our event study includes wildfires, for which there has been no previous wildfire in the same

ZIP code in the previous 12 months. The control group consists of mortgages without exposure to wildfires but from the states experiencing some wildfires. Using the matched sample, we run a two-way fixed-effects difference-in-differences (DiD) regression:

$$\begin{aligned} \text{Mortgage Event}_{i,t} = \alpha_i + \lambda_{i,t} + \beta_1 \text{Wildfire}_{it} \times \text{PRE}_t + \beta_2 \text{Wildfire}_{it} \times \text{POST}_t + \\ + \beta_3 \text{Mortgage Characteristics}_{it} + \epsilon_{i,t} \end{aligned} \tag{2}$$

where Wildfire_{it} represents a ZIP-code level wildfire covering 10% of the ZIP code area, α_i denotes mortgage fixed effects, and $\lambda_{i,t}$ indicates county $\times$ year-month fixed effects. $\text{Mortgage Event}_{i,t}$ corresponds to either foreclosure or prepayment, as defined above. PRE_t covers the nine months before the wildfire starts, and POST_t spans the 12 months following the wildfire start month.

Several crucial features distinguish this model in a typical two-way fixed-effects DiD design. Mortgage fixed effects account for time-invariant mortgage characteristics, such as borrower financial health at origination or mortgage type. Instead of time fixed effects, we apply county $\times$ year-month fixed effects to capture time-varying local economic factors at the county level, including variables such as time-varying local income or employment. To have intensive level of fixed effects, we run equation (2) using linear probability model. We also apply propensity-weighted least squares (PSWLS) regression with propensity scores, PS3 as weights from Table 2. PSWLS enables us to compare treated mortgages with a control group with similar climatological and geographic conditions determined by the wildfire propensity regressions.

3.2 Findings on Mortgage-Level Cash Flows

Wildfires and Foreclosure Probability

We first analyze the foreclosure probability by estimating equation (2) using more than 29 million mortgage-month observations. The results are reported in Table 3. In regression (1), we introduce a single post-wildfire dummy alongside extensive fixed effects, imposing stringent model constraints. We progressively introduce pre-wildfire dummies in regressions (2) and (3). Regressions (3) and (4) further segment the post-wildfire dummy into two periods: immediate (0 to 3 months post-event) and delayed (4 to 12 months post-event). Our analysis primarily focuses on the delayed period (4 to 12 months) to capture the comprehensive economic implications of wildfires. Additionally, regression (4) splits the pre-wildfire dummy into recent (-1 to -3 months) and earlier periods (-4 to -9 months) to scrutinize potential pre-trends.[14]

Regressions (1) and (2) indicate an incremental foreclosure probability increase between 0.45 and 0.50 percentage points within 12 months following wildfires, statistically significant at the 1% level. The incremental and delayed impact (months 4 to 12) intensifies to approximately 0.58 percentage points, maintaining robust statistical significance. Regarding pre-trends, pre-wildfire

[14]For -9 month, we combine -9 to -12 months to smooth the early pre-wildfire periods.

coefficients remain economically small and largely statistically insignificant, except in regression (2), where a slight negative pre-wildfire effect emerges. Nonetheless, coefficient difference tests robustly demonstrate that post-wildfire impacts significantly exceed observed pre-wildfire effects. These results suggest that wildfires cause meaningful increases in incremental foreclosure probabilities. Importantly, our results are net of unobservable time-varying county-level unobservables and time-invariant mortgage and borrower characteristics.

[Table 3 about here.]

To further elucidate these dynamics, Figure 5 illustrates the monthly evolution of incremental foreclosure probabilities from 9 months preceding to 12 months following wildfire events. Foreclosure probability distinctly rises beginning immediately post-event, sharply ascending to approximately 0.70% by month four, and subsequently stabilizing around 0.8% by month 12. Crucially, we observe no discernible pre-trend prior to wildfire occurrences, as evidenced by the stability of coefficients around the zero baseline. Collectively, these findings demonstrate a persistent, economically substantial impact of wildfires on foreclosure likelihood across the US. Among mortgage characteristics that vary over time, we find that loan balance has a statistically significant impact on foreclosure probability.

[Figure 5 about here.]

Prior wildfire literature predominantly focuses on California, raising questions about generalizability. To address this concern, we partition our sample into California and non-California mortgages and separately estimate equation (2). Figure 7 presents these comparative analyses.

Our results consistently indicate significant foreclosure probability increases post-wildfire in both California and the rest of the US. Specifically, foreclosure likelihood elevates by 0.80–0.84% over twelve months post-wildfire events in both subsamples. Notably, the wider confidence intervals observed for the non-California sample reflect greater variability in wildfire impacts outside California. Importantly, neither subsample demonstrates meaningful pre-trends economically or statistically, further reinforcing that observed foreclosure effects are genuinely attributable to wildfire events rather than pre-existing conditions.

[Figure 7 about here.]

Wildfires and Prepayment Probability

We next examine the impact of wildfires on mortgage prepayment probabilities, following a similar empirical framework as in our foreclosure analysis. The results from these regressions, which incorporate extensive fixed effects and pre- and post-wildfire dummies, are presented in Table 4.

Our findings indicate a substantial and statistically significant increase in prepayment probability following wildfires, ranging from 2 to 2.5 percentage points within 12 months post-event.

We identify statistically significant pre-wildfire effects, although their magnitudes are notably smaller relative to post-wildfire impacts. Specifically, the pre- and post-wildfire dummy coefficients differ by approximately 2.5 to 2.8 percentage points, significant at the 1% level. Crucially, recent months immediately preceding wildfires (-1 to -3 months) display no statistically significant pre-trend, reinforcing the robustness of our causal interpretation.

[Table 4 about here.]

It is economically intuitive to observe some pre-trend impacts in earlier months (-5 to -9 months). Unlike foreclosures, which carry severe economic and reputational consequences for borrowers, prepayments primarily reflect borrower preferences and proactive risk management. Borrowers in wildfire-prone areas may reasonably anticipate future wildfire risks, prompting proactive property sales and mortgage prepayments. Indeed, the timing of these earlier months aligns with prior wildfire seasons, providing plausible economic justification for observed pre-trends.

To further explore this dynamic, Figure 6 illustrates monthly prepayment probabilities spanning nine months before to twelve months after wildfire events. Our visualization demonstrates an immediate rise in prepayment likelihood post-wildfire, ultimately exceeding a 3% incremental increase within one year.

[Figure 6 about here.]

Although a modest pre-event elevation of around 1% is detected at month -9, this minor pre-trend dissipates closer to the event, displaying no statistical significance from month -6 onwards. We attribute such early pre-event effects to borrower anticipation driven by previous wildfires or heterogeneous beliefs about climate risk. Unlike foreclosure, which borrowers typically seek to avoid due to its severe consequences, prepayment is a rational forward-looking financial decision, possibly influenced by prior nearby wildfire experiences.

To confirm generalizability, we analyze geographic heterogeneity by splitting the sample into California and non-California mortgages (Figure 8). Our findings robustly show incremental prepayment increases up to 3% in California and even greater (up to 5%) in the rest of the US. Notably, pre-event coefficients near wildfires remain insignificant, adding robustness to a clear causal impact of wildfires on mortgage prepayment decisions. The wider confidence intervals in non-California regions further highlight geographic variation in wildfire impacts.

[Figure 8 about here.]

Collectively, our results broaden the existing literature, extending insights beyond California and robustly demonstrating that wildfires substantially elevate mortgage prepayment (by approximately 3%) and foreclosure probabilities (by approximately 0.8%) within one year post-event. These empirical estimates will be incorporated to our subsequent analysis of mortgage-backed security structuring to effectively manage and mitigate wildfire risk.

Loss in a Foreclosure

Having established that wildfires significantly elevate the probabilities of foreclosure and prepayment, we now examine their impact on losses conditional upon foreclosure. Wildfires pose direct physical threats to properties and may simultaneously weaken local economic conditions, potentially magnifying losses incurred upon foreclosure.

To empirically test this hypothesis, we regress the loss-to-balance ratio (conditional on foreclosure occurrence) on a wildfire event indicator. We truncate losses to 120% with reported losses exceeding 120% and ignore losses in the absence of foreclosure events to diminish the impact of outliers and focus on losses following foreclosures. Because our analysis focuses exclusively on foreclosed mortgages, we explicitly control for selection bias by incorporating the predicted probability of foreclosure as a correction term derived from the first-stage foreclosure regression, following the methodology introduced by Olsen (1980).[15]

Our regression results, presented in Table 5, demonstrate robust evidence that wildfires materially amplify foreclosure losses. Across specifications, we introduce deal fixed effects to account for variations in originator risk preferences, state fixed effects, and year-month fixed effects (regressions 1 and 2). In regressions 3 and 4, we employ interacted state fixed effects with year-month fixed effects, thereby controlling for time-varying state-level unobserved heterogeneity. Additionally, regressions (2) and (4) incorporate the selection correction term (1 - fitted foreclosure probability) following Olsen (1980) and control comprehensively for mortgage characteristics at the time of foreclosure.

The empirical estimates indicate that wildfire events significantly increase the loss-to-balance ratio by approximately 3.9% to 4.5%. Translating these results into economic terms, we find an unconditional recovery rate of approximately 63% following a typical foreclosure. However, the presence of a wildfire event reduces this recovery rate below 59%. We subsequently integrate these empirically derived recovery rate adjustments into our mortgage-backed security optimization model to account explicitly for wildfire risk.

[Table 5 about here.]

Among the other mortgage-level controls, we find that higher interest rate, higher LTV, and longer time to maturity significantly increase loss. On the other hand, loans with lower balance have lower loss. We do not find consistently significant impact for FICO and adjustable-rate mortgages.

[15] To preserve sample size, we employ separate state and year-month fixed effects rather than their interaction.

4 MBS Deals' Exposure to Wildfires: Deal Loss, Diversification, and Spatial Correlation

The previous section estimated economically and statistically significant impacts of wildfires on prepayments, defaults, and losses. Whether this risk has a significant impact on deal cash flows is an empirical question. We first measure the exposure of deals to wildfires, and document whether wildfire shocks affect deal cash flows causing losses using a deal-level event study design. We then provide evidence that is related to the within-MBS deal spatial correlation in wildfire risk exposure.

4.1 Deal-Level Wildfire Exposure

We first measure a deal's realized dollar exposure. Deals are exposed due to correlated risks, due to large dollar concentrations in exposed geographic areas, and due to time series correlation. This is captured by breaking down the components of the variance of MBS deal exposure.

MBS Deal Exposure: the Role of Correlation and Concentration

We measure the exposure of MBS using the dollar value of mortgages' unpaid principal balance that is located in affected 5-digit ZIP codes. Treated 5-digit ZIP codes are defined as in the mortgage-level in Section 3. The share of an MBS affected by such wildfire exposure in month t is then estimated as using such treated ZIP codes:

$$\text{MBS Share Affected}_{jt} = \frac{\sum_{i=1}^{N_j} \text{Balance}_{jit} \text{Treated ZIP}_{\ell(i)t}}{\sum_{i=1}^{N_j} \text{Balance}_{jit}} \tag{3}$$

where $\ell(i)$ is the location of mortgage i, ℓ indexes 5-digit ZIP codes, j is the deal, and Balance_{jit} is the unpaid principal balance of mortgage i for MBS j at the beginning of time t. Analyzing the ex-ante distribution of this treatment allows us to pin down the drivers of MBSs' exposure to wildfire.

A key driver of tail events in MBS deal exposure is the possibility that multiple locations within a deal are affected at the same time, i.e. in a correlated fashion. This becomes apparent when considering the ex-ante distribution of the random variable $\widetilde{\text{Wildfire}}_{jt}$ for deal j in month t, the aggregation of wildfire shocks for each mortgage. The deal-level wildfire occurrence is the sum of the dollar weighted-exposure of individual mortgages $i = 1, 2, \ldots, N_j$:

$$\widetilde{\text{Wildfire}}_{jt} = \frac{\sum_{i=1}^{N_j} \text{Balance}_{ijt} \widetilde{\text{Wildfire}}_{\ell(i)t}}{\sum_{i=1}^{N_j} \text{Balance}_{ijt}} = \sum_{i=1}^{N_j} b_{ijt} \widetilde{\text{Wildfire}}_{\ell(i)t}, \tag{4}$$

where $\widetilde{\text{Wildfire}}_{\ell(i)t}$ is a random variable equal to 1 whenever a wildfire hits location j, and zero otherwise.[16]

We can see the benefits of pooling risk. Denote by:

$$W_{lt} = \mathbb{E}\left[\widetilde{\text{Wildfire}}_{\ell(i)t}\right], \tag{5}$$

the probability that a wildfire hits location l, and by:

$$\rho_j = \text{Corr}\left[\widetilde{\text{Wildfire}}_{\ell t}, \widetilde{\text{Wildfire}}_{\ell' t}\right], \tag{6}$$

the correlation that any pair l, l' of locations of MBS j experiences a wildfire in the same time period. The variance of deal-level wildfire exposure depends on the (i) correlation between locations and on the (ii) concentration of risk:

$$\begin{aligned}\text{Var}(\widetilde{\text{Wildfire}}_{jt}) \quad &= \quad \underbrace{\rho_j \left\{2 \sum_{i<i'} b_{ijt} b_{i'jt} W_{\ell(i)t}(1 - W_{\ell(i)t}) W_{\ell(i')t}(1 - W_{\ell(i')t})\right\}}_{\textbf{Spatial Correlation}} \\ &+ \quad \underbrace{\sum_{i=1}^{N_j} b_{ijt}^2 W_{\ell(i)}^2 (1 - W_{\ell(i)}^2)}_{\textbf{Herfindahl of Spatial Concentration}}\end{aligned} \tag{7}$$

The first term is a term due to the correlation of wildfire risk. The second term is akin to a Herfindahl index, measuring the dispersion of dollars of balance across locations. The Herfindahl index $\sum_{i=1}^{N_j} b_{ijt}^2$ will be minimum when the dollar balance is spread equally across locations.

To see clearly where pooling helps (and does not), consider the case where mortgages have equal sizes, so that the total balance B is split across N mortgages. Also simplify by assuming equal probabilities across locations. Then:

$$\text{Var}(\widetilde{\text{Wildfire}}_{jt}) = \underbrace{\rho_j \frac{N-1}{N} W^2 (1 - W)^2}_{\text{Correlation Term, stays finite as } N \to \infty} + \underbrace{\frac{1}{N^2} W^2 (1 - W)^2}_{\text{Vanishes as } N \to \infty} \tag{8}$$

and we can see that the first correlation term stays finite as the number of mortgages increases to infinity. Thus deal-level pooling of wildfire can reduce the variance of risk whenever the correlation of risk stays small compared to the number of mortgages N.

A fast method to estimate the within-deal correlation is by using the regression coefficient of wildfire occurrence on average wildfire occurrence for other ZIPs of the MBS:

$$W_{j\ell t} = \text{C}_j^{\text{st}} + \beta_j \overline{W_{j-\ell t}} + \varepsilon_{j\ell t} \tag{9}$$

[16] Section 3 provides multiple definitions for this treatment, based on the surface, dollar value of housing units, or number of housing units within the wildfire perimeter.

where $\overline{W_{j-\ell t}}$ is the average frequency of wildfires in other locations of the MBS deal j at time t. The regression is weighted by deal's dollar balances $b_{j\ell t}$ in each location. This method yields the correct deal-level correlation as the regression coefficient is:

$$\beta_j = \frac{\mathrm{Cov}(W_{j\ell t}, \overline{W_{j-\ell t}})}{\mathrm{Var}(\overline{W_{j-\ell t}})} = \underbrace{\rho_j}_{\text{Deal-Level Correlation}} \times \sqrt{\frac{\mathrm{Var}(\overline{W_{j-\ell t}})}{\mathrm{Var}(W_{j\ell t})}} \tag{10}$$

4.2 Estimating the Impact of Wildfires on Deal-Level Cash Flows

Identifying the impact of wildfire exposure on deal cash flows is challenging for at least two reasons. First, deals cover extensive geographic areas, and may thus be exposed to a large number of multiple treatments. An MBS deal's wildfire exposure evolves over time as the distribution of unpaid principal balances across locations evolves as households prepay and default at different speeds. Deals may be structured at origination in ways that correlate with wildfire propensity. They may also reflect other aspects of climate change adaptation, such as the ability of the lender to renegotiate the terms of the mortgage or allow for forbearance.

Second, multiple wildfires may occur in the same month or in different months, precluding the construction of event studies with non-overlapping treatments. We address these challenges by building an event study where we focus on the wildfire shocks that affect each deal most. We then compare these treated MBS deals to control MBS deals with similar wildfire propensity at the time of exposure.

Treated Deals

The MBS industry has described potential wildfire exposure since at least the early 2000s. A common method in the industry is to count the % of the deal's balance in locations affected by a wildfire. This is from the 2007 prospectus of a deal of Credit Suisse loans serviced by Wells Fargo:

“ **Thornburg Mortgage Securities Trust. Mortgage Loan Pass-Through Certificates, Series 2007-5. Page S-24.**

Wildfires in California may adversely affect holders of the certificates

As of the date of this prospectus supplement, vast regions of Southern California from north of Los Angeles to south of San Diego are experiencing multiple extensive wildfires resulting in significant property damage and the evacuation of close to one million residents. President Bush has declared a state of federal emergency for the counties of Los Angeles, Orange, Riverside, San Bernardino, San Diego, Santa Barbara and Ventura, entitling them to federal disaster assistance under FEMA. Approximately 15.43%, 13.39% and 11.70% of mortgage loans (by aggregate unpaid principal balance as of the cut-off date) in loan groups 1, 2 and 3, respectively, are secured by mortgaged properties located in these counties. In addition, other counties may have been or may become affected by the wildfires. "

We adopt this industry standard in this paper. Figure 9(a) presents the number of deals for which the ZIPs treated represent more than 5% of the unpaid principal balance of the MBS deal. Figure 10 presents the same statistics by month for three different thresholds.

$$\text{Treated}_{dt} = \mathbf{1}\left(\frac{\sum_{j=1}^{J} \text{Balance}_{djt}\text{Treated ZIP}_{jt}}{\sum_{j=1} \text{Balance}_{djt}} > \text{Threshold}\right) \tag{11}$$

For each month for which there is at least one MBS deal treated, observations of the treated deals in the window of -12 to $+36$ months is considered.

[Figure 9 about here.]

[Figure 10 about here.]

Wildfire Exposure and Cumulative Loss of Deals

Extending our mortgage-level analysis to the deal level, we examine the cumulative loss of a deal as a share of its principal balance at origination.[17] Given that deals may be exposed to multiple wildfire events across different times and ZIP codes, we focus on the single most severe wildfire shock per deal—defined as the month in which one or more fires collectively affect the greatest outstanding balance of that deal.

Treated deals are those in which at least 5%, 10%, or 15% of the outstanding principal balance is impacted by wildfires. Control deals are those either unaffected or affected by less than 5% of their balance. To isolate wildfire-driven variation, we estimate the following two-way fixed effects model:

$$\begin{aligned} \text{Cumulative Deal Loss}_{dt} = \alpha_i + \lambda_{dt} + \beta_1 &\text{Deal-Level Wildfire Shock}_{dt} \times \text{PRE}_t \\ &+\beta_2 \text{Deal-Level Wildfire Shock}_{dt} \times \text{POST}_t \\ &+\beta_3 \text{Weighted Deal Characteristics}_{dt} + \epsilon_{dt} \end{aligned} \tag{12}$$

where Cumulative Deal Loss$_{dt}$ is a measure of the share of cumulative losses as a fraction of the deal's principal balance at origination. Deal-Level Wildfire Shock$_{dt}$ $= 1$ when deal d has been exposed to a wildfire event. A wildfire event is considered when at least one deal has had more than 5%, 10% or 15% of its unpaid principal balance affected by a wildfire. The control group is built by considering the set of never treated deals throughout the period and the deals that are affected

[17] We winsorize by 1% due to some outliers.

by less than 5%. PRE_t and POST_t are the months before and after the month the first wildfire affecting the deal starts. The regressions include deal and year-month fixed effects representing a two-way fixed effects DiD model.

The year-month fixed effects control for macro trends that impact cash flows and are statistically correlated with wildfire exposure. The year-month fixed effects also control for seasonal effects: as wildfires occur in specific months of the year, during so-called hot seasons of housing markets (Ngai & Tenreyro 2014), this may be correlated with cash flows. The deal fixed effects control for deal-specific unobservables that may be correlated with wildfire exposure and cash flows: these include deals located in specific fire-prone parts of the US that may also be affected by different trends in house prices, household mobility. We also control for deal-level mortgage characteristics weighted by individual mortgage balances. Standard errors are clustered at the deal level and weighted by wildfire propensity scores, which are weighted by mortgage balance at the deal level.

[Table 6 about here.]

Similar to mortgage-level analysis, we start with post- and pre-wildfire dummies. The results are presented in Table 6. Regressions (1) and (2) are based on treated deals that are at least 5% affected, while regressions (3) and (4) are for at least 10% affected, and regressions (5) and (6) are for at least 15% affected. Our findings indicate that treated deals that are affected by at least 5% of the deal balance have no statistically significant loss. On the other hand, as we increase the threshold for treated deals to 10% and 15%, respectively, we start to observe that treated deals have statistically significant losses. For treated deals that are affected by at least 15%, we find that wildfire shocks increase cumulative losses by 26% and 45% at 1% significance level in the second and third years, respectively, as opposed to control deals. Importantly, pre-treatment coefficients across these specifications are small and statistically insignificant, confirming the absence of pre-trend concerns.

Overall, two primary patterns emerge from our results. First, as we increase the threshold, the statistical significance and magnitude of deal losses increase monotonically. Second, losses accumulate over time with little short-run impact, but material effects by the second and third years. We start to observe statistically significant impacts by the second year and the impacts become larger in the third year. Compared to mortgage-level results, this is expected as the losses appear after some attempts for resolution. Economically, we see that foreclosure of mortgages is more likely towards the end of the first year following a wildfire. Realizing losses also take time, so the impact of a wildfire on deal losses kicks in by the second and third years.

We then turn to Figure 11. In panel (a), we present the results of analysis using treated deals that are affected by more than 5% of a deal. In panel (b), we use deals that are affected by more than 10% of the deal balance and similarly excludes deals that are affected by between 5% and 10%. Similarly, in panel (c), we present the results for treated deals affected by more than 15% and we exclude deals that are affected by between 5% and 15%. The event time used ranges from month t-9 to t+36.

[Figure 11 about here.]

Consistent with Table 6, as the threshold for treated deals increase, we observe more statistically and economically significant impacts. All panels reflect that the early months following the wildfire do not constitute any statistically significant impact on deal losses. However, the losses start to increase thereafter. Across all panels, losses mainly remain flat prior to the wildfire, reinforcing the absence of significant pre-trends. Overall, our findings demonstrate that the increased probability of foreclosure following wildfires is carried over the deals similarly with larger losses following a wildfire affecting a deal. These results are central to understanding MBS risk, and we build on them in the next section by proposing a wildfire-propensity optimized MBS structuring approach.

Treated Deals and Spatial Concentration

Table 7 describes how the spatial concentration of originations in MBS deals leads to wildfire exposure. Our findings suggest that deals that are treated have higher level of within-deal spatial correlation (fires occuring at the same time across the ZIP codes of the deal), a higher level of concentration of dollars in a small number of ZIP codes, measured by the Herfindahl index of origination volumes; and such deals tend to have mortgages in a smaller number of ZIP codes.

$$\begin{aligned}\text{Treated}_{dt} &= \text{Constant} + b_1\text{Spatial Correlation}_d + b_2\log(\text{Herfindahl}) \\ &\quad + b_3\log(\#\text{ ZIPs in Deal}) + b_4\log(\text{Deal Balance at Origination}) + \text{Residual}_{dt} \quad (13)\end{aligned}$$

The result of this regression is presented in column (2). Deals with a correlation of 1 tend be 40 percentage points more likely to be treated. Deals with a 10-percentage-point increase in the Herfindahl index are 0.80 percentage points more likely to be treated. Deals with 10% more ZIPs in the deal tend to be 1.7 percentage points less likely to be treated. Larger deals are more likely to be treated *ceteris paribus*. Thus, conditional on deal size, the margins of spatial correlation, the herfindahl, and the number of ZIPs can make it less likely that the deal is treated. Column (1) regresses the maximum of the unpaid principal balance of the deal exposed to wildfires on the same covariates. Signs are similar. Column (3) suggests that, consistent with standard microeconomic theory, the larger number of ZIPs in a deal leads to a lower Herfindahl index and, in column (4), a lower within-deal spatial correlation.

[Table 7 about here.]

Our findings in Table 7 demonstrate that within-deal spatial correlation increases the likelihood of a deal to be treated – being exposed to wildfire risk. On the other hand, in Figure A, we evaluate the variation in within-pool or -month spatial correlation. Panel (a) shows whether the size of originators is correlated with within-pool spatial correlation. We observe that the largest originators can lower within-pool spatial correlation. Panel (b) presents within-month spatial correlation. We observe that within-month autocorrelation has increased by years. One caveat in this descriptive analysis is the availability of geographic data provided by originators and sponsors, almost 100% until 2015, decreases after 2015.

[Figure A about here.]

5 Designing MBS Deals using Portfolios of Mortgages

Pooling mortgages from across the US may enable a diversification of risk, as such pooling averages out the idiosyncratic risk of individual mortgages. As wildfire risk increases in specific locations due to climate change, such diversification tools enable investors to adapt to climate change by picking more diversified pools. How can we design Mortgage-Backed Securities that offer a given profile of risk and return? Depending on the risk preferences of the investor, should such Mortgage-Backed Securities be exposed to wildfire risk on top of the existing interest rate and credit risks?

This section presents and solves numerically this pooling problem over the 5-digit ZIP codes of the coterminous US, by calculating the risk and return of an MBS deal with any arbitrary weight in each of thousands of ZIP Code Tabulation Area.

Choosing an MBS is akin to solving a portfolio problem, where the individual securities are mortgages across the US. Each location has a specific baseline prepayment and foreclosure rate, a sensitivity of prepayment to future mortgage rates, and potential wildfires that affect prepayment and foreclosure. These parameters have been estimated in the previous sections. In turn, this yields possible 5-digit ZIP code cash flows: their average, standard deviation, and other moments such as skewness and kurtosis. These cash flows are correlated across locations, as wildfires occur in a correlated fashion and as interest rate risk potentially affects the prepayment probabilities of all pools at different margins. By combining mortgages from locations across the US, we can calculate the set of possible expected returns and risk profiles. By using the IPCC's forecast of temperatures in 2050, we can measure, for each simulated pool, the impact of such increasing wildfire risk on risk, return, and the Sharpe ratio of these pools. Pools can be built to be resilient to climate risk. A key takeaway of this section is that such pools have non-zero exposure to wildfire risk as areas with higher risk tend to have lower baseline prepayment rates. The method produces maps of dollar allocations for any arbitrary target Sharpe ratio, and any target DCF of cash flows and should be a guide for investors.

Wildfire risk causes prepayments and foreclosures for individual mortgages. Interest rates affect the probability of prepayment and foreclosure at the mortgage level. Credit risk causes increases in foreclosure rates as well. We simulate the local and spatially correlated wildfire shocks in each 5-

digit ZIP code, either during a scenario of stationary wildfire probabilities (2010–2021 probabilities), under a scenario of higher temperatures (IPCC models CMIP6) in 2050. We also model the dynamics of interest rates, using a Heath, Jarrow & Morton (1990) approach that forecasts the entire yield curve using four factors; and the premium of the 30-year FRM over the 10-year Treasury using a Cox, Ingersoll Jr & Ross (2005) process.

This section shows that pooling can significantly alleviate the impact of rising wildfire risk on MBSs' rate of return. As temperatures increase, this causes a decline in returns and an increase in risk *without rebalancing*. Yet, when MBS pools are re-optimized, the impact on returns and risks is significantly smaller.

5.1 A Portfolio Problem

We focus on designing a security that offers a profile of risk and return, characterized by the probability distribution of its stochastic return $\tilde{R}$. This probability distribution is affected by the probability of prepayment and foreclosure each month, and the recovery rate conditional on a foreclosure.

To solve this pooling problem, we build a dataset of cash flows and notionals for each 5-digit ZIP code over 360 months (30 years) and across 20 simulations of correlated wildfires across ZIP codes, interest rates, and the 30-year FRM premium. The return of holding mortgages in each location is computed for each month and each simulation, and the optimal pool is a trade-off between (a) the expected average return over the life of the pool and across simulations and (b) the expected risk, typically measured using the standard deviation. In an extension we also use the skewness and the kurtosis of returns (Kraus & Litzenberger 1976, Chang, Monahan, Ouazad & Vasvari 2021, de Silva, Larsen-Hallock, Rej & Thesmar 2025) as fixed income investments such as Mortgage-Backed Securities have, by construction, skewed and leptokurtic returns. We model our mortgage-level cash flows on Chernov et al. (2018).

MBSs as a Mean-Variance Optimization Exercise An MBS is modeled as the outcome of a Markowitz (1952), Markowitz (1959) portfolio problem. Denote by w_{j0} the share of origination dollars allocated to location $j = 1, 2, \ldots, J$ (a 5-digit ZIP code). We assume $w_{j0} \geq 0$ as we do not allow the short-selling of mortgages. We allow zero allocations. Denote by $\boldsymbol{\mu}$ the vector of mean monthly returns, of size J; and by $\boldsymbol{\Sigma}$ the variance-covariance of returns across locations, a square matrix of size J. Returns are correlated across locations as households' prepayment and default behavior depends on the dynamic of interest rates and by correlated wildfire risk. The returns are imperfectly correlated across locations as the sensitivity of prepayment and default hazard rates depends on each location j.

The goal of this section is to find the allocation of origination dollars that maximizes the mean-variance objective.

$$\max_{\mathbf{w}_0} \quad \mathbf{w}_0'\boldsymbol{\mu} - \frac{1}{2}\rho\mathbf{w}_0'\boldsymbol{\Sigma}\mathbf{w}_0 - \xi\mathbf{w}_0'\mathbf{w}_0 \tag{14}$$

$$\text{s.t.} \quad \mathbf{w}_0'\mathbf{1} = 1 \tag{15}$$

$$\text{s.t.} \quad w_{j0} \geq 0 \qquad \forall j = 1, 2, \ldots, J \tag{16}$$

where $\rho > 0$ is investors' risk aversion. The subscript 0 in $\mathbf{w}_0$ denotes that the allocation is fixed at origination. The dollars at each location vary across time t due to prepayment and foreclosure. Other types of pools (e.g. some types of covered bonds) can have time-varying optimal weights. Once optimal weights $\mathbf{w}_0$ of dimension J are found, we can summarize the results by reducing the dimension using a Koijen & Yogo (2019) demand system.

MBS prospectuses typically include provisions requiring a maximum weight per 5-digit ZIP code, thus ensuring that the portfolio does not exhibit excess geographic concentration. Yet, the Markowitz (1952) framework is known to require adjustments to yield portfolios without excess concentration in one or a few outlier assets. This has led to an extensive literature on improvements over the basic Markowitz approach (Black & Litterman 1992, Lopez de Prado 2016, Yin, Perchet & Soupé 2021). In the case of this paper, regularization yields realistic levels of diversification. First, the discrete and lumpy nature of mortgage originations means that each location requires a minimum amount of investment. Second, the outperformance of a specific location may be driven by outliers (Kim, Kim, Lee, Kim & Fabozzi 2024), leading to portfolios with excess concentration in specific areas. The parameter ξ can be adjusted to target a specific degree of concentration.

Solving for the optimal portfolio (14) may yield portfolios that exhibit excess diversification or concentration relative to observed Mortgage-Backed Securities. The regularization term $\xi\mathbf{w}_0'\mathbf{w}_0$ is typical in recent literature (Caccioli, Still, Marsili & Kondor 2013) and enables us to control the degree of aggregate concentration or diversification to match realistic average origination volume by location.

Cash Flows The cash flow $\widetilde{\text{CF}}_{jt}$ of mortgages originated at location j in year-month t is:[18]

$$\widetilde{\text{CF}}_{jt} = \underbrace{\widetilde{N}_{j,t}c_j}_{\text{Scheduled Payments}} + \underbrace{\widetilde{\lambda}_{j,t}\tilde{\alpha}_{j,t}I_{j,t}}_{\text{Unscheduled Payments}} \tag{17}$$

$\widetilde{N}_{j,t}$ is the dollar notional at location j in month t. c_j is the coupon rate in location j. When mortgages are fixed rate mortgages (FRMs), the coupon rate is:

$$c_j = \frac{m_{j0}^{30y}(1+m_{j0}^{30y})^T}{(1+m_{j0}^{30y})^T - 1} \tag{18}$$

[18] $\tilde{x}_t$ indicates that the variable x is stochastic.

The coupon rate is fixed at origination.

$\widetilde{\lambda}_{j,t} \in [0,1]$ is the hazard rate of prepayment and foreclosure. It is ex-ante a sequence of random variables for each future month $t = 1, 2, \ldots, 360$. The notional $\widetilde{N}_{j,t}$ in each location declines at a speed equal to the hazard rate $\widetilde{\lambda}_{j,t}$, as:

$$\widetilde{N}_{j,t+1} = (1 - \widetilde{\lambda}_{j,t})\widetilde{N}_{j,t} \tag{19}$$

The quantity $\alpha_{j,t} \in [0,1]$ is the recovery rate. It measures the share of the unpaid principal balance that is recovered in case of a prepayment or default. It is also a random variable that declines when a wildfire occurs, consistent with the results of Section 3.2. When mortgages prepay only, or when the MBS is a GSE pool, $\alpha_{j,t} = 1$. For private-label MBS deals, the investor may lose part of the balance, and $\alpha_{j,t} \leq 1$. See Fuster, Lucca & Vickery (2023) for a description of the differences in credit risk exposure across different types of pools (GSE, PLS RMBS, CRTs, covered bonds, and other pools).

Returns and Empirical Estimates of $\hat{\boldsymbol{\mu}}$ and $\widehat{\Sigma}$ For returns, we use the yield-to-maturity of each location j at origination, denoted R_{j0}, as one of the two approaches of this paper. The approach using total returns is described later in the section. The yield-to-maturity is pinned down by the sequence of cash flows $\widetilde{\mathrm{CF}}_{jt}$, for a given notional lending of N_0. For each stochastic sequence of cash flows, the yield-to-maturity is:

$$\tilde{R}_{j0} = \tilde{R}_{j0}(\widetilde{\mathrm{CF}}_{j1}, \widetilde{\mathrm{CF}}_{j2}, \ldots, \widetilde{\mathrm{CF}}_{jT}) \qquad \text{s.t.} \qquad N_0 = \sum_{t=1}^{T} \frac{1}{(1 + \tilde{R}_{j0})^t} \widetilde{\mathrm{CF}}_{jt}. \tag{20}$$

Then the average yield-to-maturity (YTM) and the variance-covariance of YTMs across locations are:

$$\boldsymbol{\mu} = [\mathbb{E}[\mathbf{R}_{j0}]]_j, \qquad \boldsymbol{\Sigma} = [\mathrm{Cov}(\mathbf{R}_{j0}, \mathbf{R}_{j'0})]_{j,j'}. \tag{21}$$

These two moments are computed using Monte Carlo simulations. For each simulation $s = 1, 2, \ldots, S$, each location $j = 1, 2, \ldots, J$ we obtain the yield-to-maturity R_{js}. The mean-variance optimization exercise (14) is conducted such Monte-Carlo estimates $\hat{\boldsymbol{\mu}}$ and $\hat{\Sigma}$ based on these S simulations. These simulations depend: (i) the simulation of risk-free yields by simulating the dynamic of the four factors of a Heath et al. (1990) factor model, (ii) the simulation of the premium of the 30-year FRM rate over a maturity-matched Treasury; this is done using a CIR process, (iii) the simulation of correlated wildfire shocks. We obtain a simulated return R_{j0s} of each location j for each simulation s at origination $t = 0$. The mean vector and the variance-covariance matrix are obtained by taking the empirical average:

$$\hat{\mu}_j = \frac{1}{S}\sum_{s=1}^{S} R_{j0s}, \qquad \hat{\sigma}_{jj'} = \frac{1}{S-1}\sum_{s=1}^{S}(R_{j0s}-\mu_j)(R_{j'0s}-\mu_{j'}) \tag{22}$$

There is an extant literature suggesting improvements over this simple approach for the calculation of the variance-covariance matrix (e.g. Ledoit & Wolf (2003) and Ledoit & Wolf (2017)). These include using shrinkage estimators, using dimensionality reduction by principal components analysis (PCA) or singular value decomposition (SVD).

The yield-to-maturity of the pool R_0 may differ from the weighted average of yield-to-maturities R_{j0} of mortgages within the pool, as the yield-to-maturity is non-linear in weighted cash flows.

Simulating Location-Specific Hazard Rates The hazard rates of prepayment and foreclosure $\widetilde{\lambda}_{j,t}$ depend on:

(i) a location-specific hazard rate, based on historical averages.

(ii) borrowers' incentives to prepay and default, based on the difference between the current mortgage rate $\tilde{m}_t^{30y}$ and the mortgage rate at origination, denoted m_0^{30y};

(iii) the occurrence of wildfires at location j.[19]

(iv) the observed month-to-month variance of hazard rates.

These two drivers of hazard rates can be modelled in a logistic regression with location-specific hazard rates, the impact of current mortgage rates, and the impact of wildfires. The location-specific hazard rate $0 < \widetilde{\lambda}_{jt} < 1$ is:

$$\log\left(\frac{\widetilde{\lambda}_{jt}}{1-\widetilde{\lambda}_{jt}}\right) = \log\left(\frac{\lambda_j^0}{1-\lambda_j^0}\right) + \zeta(m_0^{30y} - \tilde{m}_t^{30y}) + \delta\widetilde{\text{Wildfire}}_{jt} + e_{jt}, \tag{23}$$

where each location has a specific base hazard rate λ_j^0. The future path of wildfires is simulated by accounting for (i) each location's specific wildfire probability (e.g. higher in California and lower in New York) and (ii) the spatial correlation of wildfires across locations. The simulation of such events across ZIP codes is described below.

The specification can account for the concavity of the relationship between mortgage rates and the hazard rate, the so-called S curve of MBSs measuring refinancing incentives (Fabozzi, Bhattacharya & Berliner 2011, Fabozzi 2016, Chernov et al. 2018, Boyarchenko et al. 2019). Additional adjustments may be required to account for the burnout effect (Hall 2000).

[19]Note that the mortgage rate at origination is absorbed by the location-specific fixed effect in the hazard rate.

When estimating the parameters of (23) for the simulation on Table A columns 2 and 4, the econometrician faces the possibility that some ZIPs do not experience prepayments or foreclosures. Hence a method is required to account for ZIP-level zeros in prepayment and foreclosure rates. We account for this by estimating a Heckman (1974) first-step regression for 'Any hazard,' where the dependent variable is equal to 1 if $\widetilde{\lambda}_{jt} > 0$, and 0 otherwise. We model this as a latent variable as in Heckman (1974).

$$\text{Any}\,\widetilde{\text{Hazard}}^{*}_{jt} = \text{Location}_j + \zeta'(m_0^{30y} - \tilde{m}_t^{30y}) + \delta' \widetilde{\text{Wildfire}}_{jt} + e'_{jt}. \tag{24}$$

with $\text{Any}\,\widetilde{\text{Hazard}}_{jt} = 1$ if $\text{Any}\,\widetilde{\text{Hazard}}^{*}_{jt} > 0$ and 0 otherwise.

The simulated hazard is equal to the product of the second term $P(\text{Any}\,\widetilde{\text{Hazard}}_{jt} = 1)$ by the predicted hazard $\widetilde{\lambda}_{jt}$ conditional on $\text{Any}\,\widetilde{\text{Hazard}}_{jt} = 1$. These results are presented on columns 1 and 3 of Table A.

Price Finally, we will simulate the price of pools. The price is the present discounted value of future cash flows, discounted by an MBS-specific discount rate, equal to the stochastic risk free rate and the option-ajusted spread.

$$\widetilde{p}_t(\mathbf{w}_0) = \sum_{t=1}^{T} \prod_{k=1}^{t} \frac{1}{(1 + \widetilde{r}_k + \text{OAS})} \widetilde{\text{CF}}_t(\mathbf{w}_0) \tag{25}$$

where $\widetilde{r}_k$ is the sequence of simulated one-month short rates, and the OAS is a fixed option-adjusted spread, as in Fabozzi et al. (2011).[20]

Total Returns as an Alternative to YTM As a robustness check, we estimate the optimal weights $\mathbf{w}_0$ using ZIP-level total returns at monthly frequency instead of the ZIP-level yield-to-maturity at origination (20). In this case, the total return of a deal in month t with initial weights $\mathbf{w}_0$ is defined as:

$$\widetilde{\mathbf{R}}_t(\mathbf{w}_0) = \frac{\tilde{p}_t(\mathbf{w}_0) - \tilde{p}_{t-1}(\mathbf{w}_0)}{\tilde{p}_{t-1}(\mathbf{w}_0)} + \frac{\widetilde{\text{CF}}_t(\mathbf{w}_0)}{\tilde{p}_{t-1}(\mathbf{w}_0)} \tag{26}$$

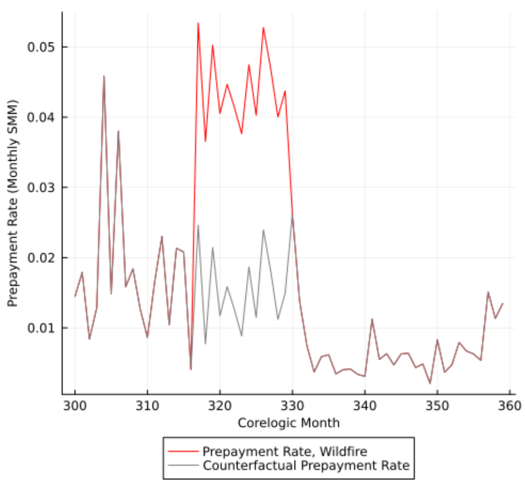
where $\tilde{p}_t$ is the price computed as in (25). We build the estimate of the expected returns by taking the average, for a given ZIP code j, of total returns across all time months $t = 1, 2, \ldots, 360$, and all simulations $s = 1, 2, \ldots, S$; and similarly for the computation of the variance-covariance matrix $\widehat{\Sigma}$.

[20] Page 213. The OAS is a fixed spread here. An alternative is to use a stochastic Option-Adjusted Spreads as in Chernov et al. (2018).

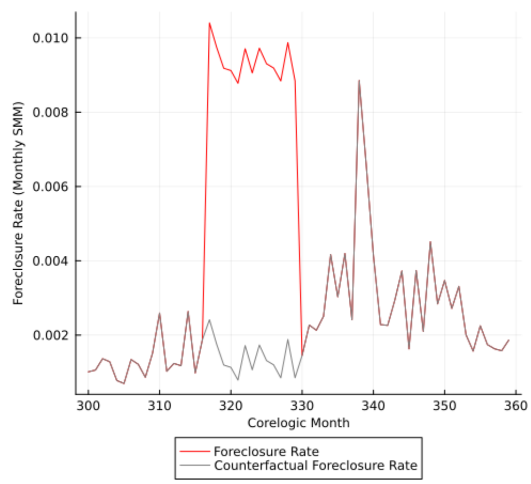
Figure 1: Simulated Prepayment and Foreclosure Rates

These figures show the paths of prepayment and foreclosure hazard rates for one ZIP code j, 83501. The upper panels focus on one simulation where a wildfire affects the ZIP code. Wildfire shocks are drawn according to the estimated Wildfire Propensity Score. The red line is the simulated hazard rate, and the black line is the counterfactual when the impact of the wildfire is removed. The lower panels show the ten different simulated hazard rates for this ZIP code. Such simulations are conducted for each of the ZIP codes of our sample.

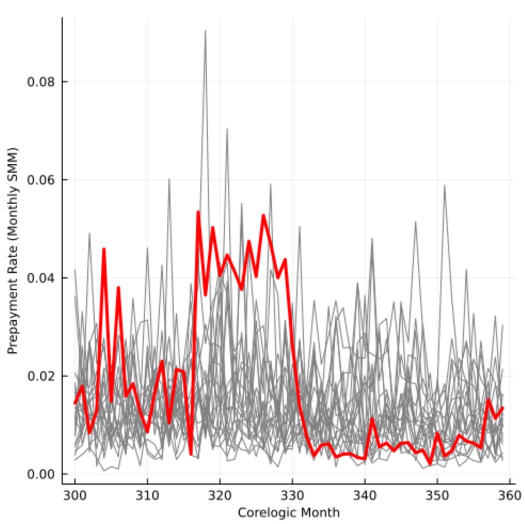
(a) Prepayment Rate and Counterfactual without a Wildfire, one Simulation



(b) Foreclosure Rate and Counterfactual without a Wildfire, one Simulation



(c) All Simulated Prepayment Paths



(d) All Simulated Foreclosure Paths

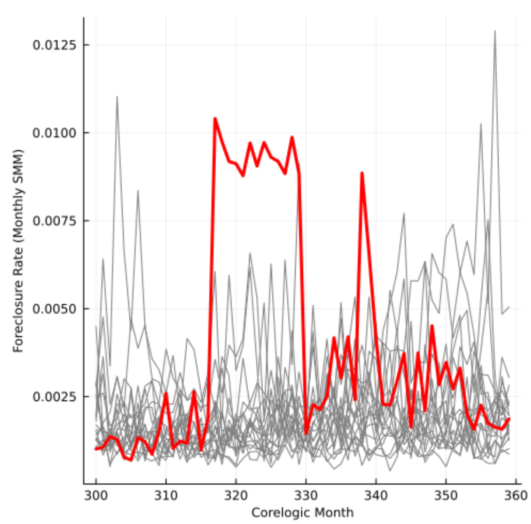


Table 1: Notations

Notation	Description
	Pool-Level Notations
$\tilde{R}_t$	Total monthly return of the pool in year-month t.
$\widetilde{\mathrm{CF}}_t$	Cash flow of the pool in year-month t.
$\tilde{p}_t$	Price of the pool in year-month t.
$\tilde{r}_{kt}$	Return of a Treasury with maturity k at time t.
OAS	Option Adjusted Spread, constant, as in Fabozzi et al. (2011).†
$\tilde{N}_t$	Notional of the pool, affected by prepayment and default.
I_t	Amortized balance without prepayment or default.
λ_t	Pool-level hazard rate of prepayment and default.
	Indices
t	Year-Month, $t = 0$ is the year-month of origination.
T	Number of months of amortization of a mortgage in the pool, typically $T = 360$.
j	Location, 5 digit ZIP code.
J	Number of possible locations. Origination dollars are allocated across $j = 1, \ldots, J$.
s	Index for Monte-Carlo simulations. Averages and covariances computed using these simulations.
	Mean-Variance Portfolio Problem
$\boldsymbol{\mu} = [\mu_j]$	Mean returns, vector of size J.
$\boldsymbol{\Sigma} = [\sigma_{jj'}]$	Variance-covariance of returns, square matrix of size J.
ρ	Investor risk aversion.
$\mathbf{w} = [w_{j0}]$	Share of the pool invested at location j, vector of size J.
$\boldsymbol{\omega}$	Koijen & Yogo (2019) portfolio coefficients.
	Location-Specific Notations
m_{j0}^{30y}	Mortgage rate at origination at location j.
c_j	Coupon rate at origination at location j.
$\tilde{\lambda}_{jt}$	Hazard rate of default and foreclosure at location j in year-month t.
$\tilde{\alpha}_{jt}$	Recovery rate, one minus lost balance at foreclosure sale, affected by wildfires.
	Heath et al. (1990) Model of Interest Rates
$P(t, T)$	At t, price of the bond maturing at T.
$f(t, T)$	At t, price of the forward rate at T.
$\tilde{\varphi}_{1t}, \tilde{\varphi}_{2t}, \tilde{\varphi}_{3t}, \tilde{\varphi}_{4t}$	Four factors for the dynamic of forward rates.
$\lambda_{1k}, \lambda_{2k}, \lambda_{3k}, \lambda_{4k}$	Factor loadings for forward rates on a grid of maturities t_k for $k = 1, 2, \ldots, K$.
	Dynamic of the 30-year FRM $\tilde{m}_t^{30y}$
$\tilde{m}_t^{30y}$	Future mortgage rate in year month t.
$\alpha^{30y}, \theta^{30y}, \sigma^{30y}$	Parameters of the Cox et al. (2005) model determining the premium of the 30-year FRM rate over the maturity-matched Treasury.

Stochastic variables denoted by a tilde $\tilde{x}$ and simulated by Monte Carlo. Bold symbols indicate vectors or matrices. †: a potential extension is to use a stochastic structure as in Chernov et al. (2018). FRM: Fixed Rate Mortgage.

Simulating the distribution of future returns hinges on simulating cash flows. Simulating cash flows relies on the simulation of the hazard rates of prepayment and default. This takes two inputs: a model of the term structure of interest rates, and a model of wildfire occurrence. We start with wildfire occurrence.

5.2 Monte Carlo Simulation of Correlated Wildfires

Wildfires are simulated by using correlated Bernoulli $\{0,1\}$ draws where each location has a specific probability of a wildfire (a specific wildfire propensity score), and wildfire occurrence has a spatial correlation $\rho_s > 0$ across locations within a state s.[21]

$$P(\text{Wildfire}_{jt}) = \text{PS}_{jt}, \quad \text{Cor}(\text{Wildfire}_{jt}, \text{Wildfire}_{j't}) = \rho_{s(j)}, \quad \text{if } s(j) = s(j') \tag{27}$$

For such probabilities we use either (i) the average Wildfire Propensity Score as estimated in Section 2.2, or (ii) wildfire propensity scores for 2050 and 2100 simulated using the IPCC's projections of temperatures in CMIP6 models. This allows to estimate the benefits of pooling in the face of rising wildfire risk.

Generating correlated 0,1 shocks for J locations with a given probability vector and a given correlation $\rho_{s(j)}$ is a classic problem in statistics (Park, Park & Shin 1996, Lunn & Davies 1998, Oman & Zucker 2001). We proceed as follows and the code is described in the appendix. We generate a multivariate normal vector of continuous variables of dimension J, with correlation $\overline{\rho}$. We compute the cumulative distribution function of each value. The c.d.f. of each variable is uniformly distributed. We then draw a wildfire for each specific location if such uniform draw is lower than the propensity score PS_{jt} for this location. We adjust the correlation $\overline{\rho}$ of the multivariate normal draws to match the desired correlation between the binary draws. We find the correlation of the normal draws that is required to achieve the target correlation ρ of 0,1 variables by a simple root finding algorithm. This completes the simulation of draws consistent with the process (27).

5.3 Simulation of Rates

We need to simulate the term structure of interest rates for two reasons. First, to discount future cash flows. Such cash flows are correlated with the rates as households prepay and default based on rates. Second, to simulate 30-year FRM rates as a premium over the maturity-matched Treasury. This is done in the next paragraph.

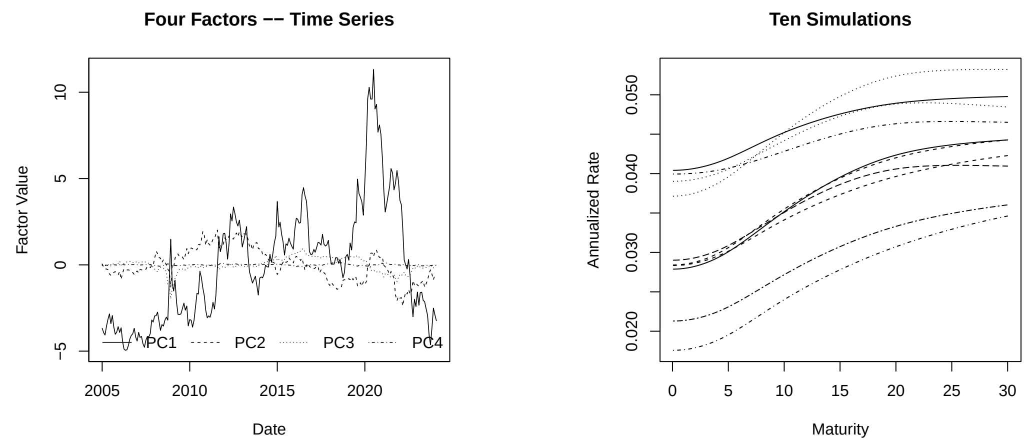
The term structure of rates is simulated using a Heath et al. (1990) approach. We first estimate forward rates using the derivative of zero coupon bond prices. This derivative is obtained by fitting a spline on the discrete grid of observed zero coupon bond prices at different maturities; and then

[21] The numerical approach to draw these correlated Bernoulli draws is described in the Appendix.

Figure 2: Rate Simulations

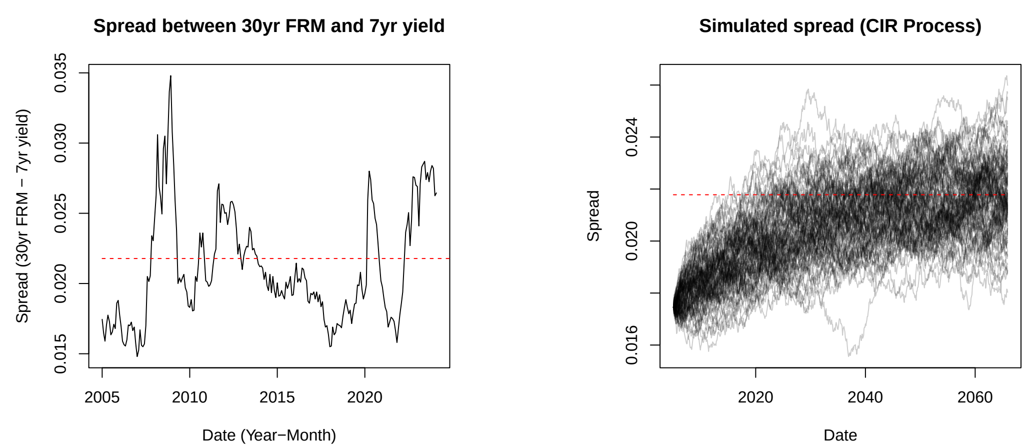
(a) Simulating Risk Free Returns using a Heath-Jarrow-Morton Approach

We simulate the term structure of risk free rates using a 4-factor model. The first step is to extract forward rates using Treasuries at maturities between 1 month and 30 years (series DGS1MO to DGS30 of FRED). The second step is to perform a factor decomposition of log forward rates. The first four factors (level, slope, curvature, hump or twist) are plotted on the first subfigure. The third step is to forecast such four factors using S simulations, using their AR(1) structure. The final step is to reconstruct the term structure. This is plotted on the second subfigure.



(b) Dynamic of the 30-year FRM and the Spread over the Maturity-Matched Treasury

The rate of the 30-year Fixed Rate Mortgage is modelled as a premium over the 10-year Treasury. The first subfigure shows that such premium is positive, that the process is mean-reverting, and its average is between 2.0 and 2.5%. The estimated parameters of the Cox et al. (2005) process is described in the body of the paper.



30-year FRM from MORTGAGE30US series from FRED, Federal Reserve Bank of St. Louis.

differentiating such a spline. This grid is:

$$t_k = \frac{1}{12} + \frac{k}{K}(360 - \frac{1}{12}), \qquad k = 0, 1, \ldots, K \tag{28}$$

where the smallest step of the grid is 1/12 to allow for a discounting at monthly frequency.

Forward rates are then analyzed using a four-factor model. This is done by Principal Components Analysis. For maturity on the grid $t_1, t_2, \ldots, t_K$, the log forward rate is a function of four factors:

$$\log f_{kt} \;= \lambda_{1k}\varphi_{1t} + \lambda_{2k}\varphi_{2t} + \lambda_{3k}\varphi_{3t} + \lambda_{4k}\varphi_{4t} + \nu_{kt} \tag{29}$$

where the factors are well-known in the literature: level, slope, convexity, and hump (see for instance Sabelli, Pioppi, Sitzia & Bormetti (2018)). The log forward rate is used, as in, e.g. Black (1995), to ensure that forward rates remain positive. Otherwise, over 360 months, simulated forward rates have a non-negligible probability of becoming negative. Analysis of time series of forward rates provided by the FRED Service (time series THREEFF1 to THREEFF10) suggest that this has not happened between January 1990 and May 2025.

Finally, we estimate the AR1 dynamics of each factor to be able to simulate their time series. The table below summarizes these findings:

Component	AR1 Constant	AR1 Coeff.	AR1 Variance	Var(Explained)
Factor 1 - Level	0.0024	0.9705	0.8075	75.99%
Factor 2 - Slope	-0.0026	0.9624	0.2591	5.91%
Factor 3 - Curvature	-0.0000	0.9525	0.1268	1.15%
Factor 4 - Twist	0.0001	0.8325	0.0257	0.01%

The first factor explains the majority of the variance, with the four factor accounting for most of the variation in forward rates.

5.4 Simulating the rate on the 30-year Fixed Rate Mortgage (FRM)

This is an input in the simulation of the hazard rates of prepayment and default. We model the 30-year FRM $\tilde{m}^{30y}_{jt}$ as a premium over the maturity-matched risk free rate. This premium is modelled as a Cox et al. (2005) to ensure that it remains positive. Over the 1971–2025 period, such premium has been negative only once, on February 28, 1980. The CIR process for the premium is modelled as:

$$d\mathrm{P}_t = \alpha^{30y}(\theta^{30y} - P_t)dt + \sigma^{30y}\sqrt{P_t}dW_t, \qquad P_t = \tilde{m}^{30y}_{jt} - r^{7y}_t \tag{30}$$

where W_t is a Brownian motion. We verify that the estimates satisfy the Feller condition $2\alpha^{30y}\theta^{30y} \geq (\sigma^{30y})^2$, which ensures positivity.

We compute the correlation between the 30-year FRM rate (MORTGAGE30US) and the 5, 7, and 10-year Treasury and find that the highest time-varying correlation is obtained with the 7-year

Treasury.[22] We thus use the 7-year Treasury plus the premium described above. The estimated CIR parameters are $\hat{\alpha}^{30y} = 0.054$, $\hat{\theta}^{30y} = 0.022$, $\hat{\sigma}^{30y} = 0.003$.

The starting point of the optimization problem matters as the information set Ω of the investor is different in each month t. We simulate the paths at the origination of the MBS, $t = 0$. The term structure of interest rates is simulated from the initial condition using a Heath et al. (1990) estimated on historical data prior to this starting point. The 30-year FRM premium over the 7-year is simulated conditional on the current premium.[23] When such forward-looking term structure is plugged-in to the hazard rate equation, this provides the forward-looking probabilities of prepayment and foreclosure.

5.5 Numerical Implementation Details

The associated code and data are provided with this paper as an archive with R and Julia code.

Data Preparation and Hazard Rate Estimation The preparation of the data is implemented using R. Hazard rates are estimated using a SQL connection to the Corelogic PLS RMBS data, and the fast *fixest* package for multi-way fixed effects. For the computation of the forward rates, we fit a smooth spline to zero coupon bond prices and then differentiate this spline with respect to the maturity. For the factor decomposition of forward rates, we perform a Principal Components Analysis of the matrix of forward rates.

Constrained Mean-Variance Portfolio Optimization When portfolio weights are constrained to be positive or zero, the optimal weights cannot be expressed in closed form. This requires a fast numerical optimizer for this J-dimensional problem. This is implemented in Julia using the JuMP package (Dunning, Huchette & Lubin 2017) with interior point optimization (Wächter & Biegler 2006), which enables a fast computation of the portfolio weights $\mathbf{w}_0$ solving for (14).

5.6 Empirical Results: Optimal and Suboptimal Portfolios

Trade-Offs Between Wildfire Exposure and Prepayment, Foreclosure Risk The portfolio optimization problem will have a non-trivial exposure to wildfire risk as there is a trade-off: households in wildfire exposed areas may have lower baseline prepayment and foreclosure risks. This is visible on Appendix Figure B. Panel (a) shows the ZIP-level average yield-to-maturity, and panel (b) displays the ZIP-level standard deviation of yield-to-maturity across Monte Carlo simulations. The first panel suggests that a substantial number of ZIP codes exhibit both high wildfire propensity scores and high yield-to-maturities. The lower tail of yield-to-maturities (ZIP codes that exhibit

[22] Time series DGS5, DGS7, DGS10, DGS20, DGS30 between 2005 and 2025. The R-Squared of the regression of MORTGAGE30US is 88.6% with DGS7.

[23] We do not reject the null hypothesis that such premium is a random walk, as the Dickey Fuller test does not reject the null, and the autocorrelogram for the first-differenced premium does not display significant AR coefficients.

negative returns in the historical data) tend to have lower average wildfire propensity scores. Panel (b) suggests that high- and low-wildfire risk areas tend to have high- and low standard deviations of yield to maturity.

The lower panels plot the prepayment and foreclosure ZIP fixed effects of specification 24. This specification estimates the probability that a ZIP code experiences one or more foreclosure or prepayments. Panel (c) presents a scatter plot of the fixed effect of the "any prepayment" specification against the wildfire propensity score. It suggests that areas with high wildfire propensity scores tend to have a lower probability of a non-zero prepayment probability. Panel (d) presents a similar scatter for the fixed effect of the "any foreclosure" specification against the wildfire propensity score. It suggests that, similarly, ZIP codes with higher wildfire propensity scores tend to have lower foreclosure fixed effects.

Overall, these four statistical facts suggest that a portfolio may want exposure to ZIP codes with a range of wildfire exposure levels.

ZIP-Level Return and Risk Figure 12, panels (a) and (b) present the distribution of average and standard deviations of ZIP-level yield-to-maturity. As described in the previous section, the yield-to-maturity is estimated for each ZIP code and simulation, and the average and standard deviations are estimated over the simulations of the same ZIP code. A portfolio of mortgages is an allocation of dollars across ZIP codes. Panel (a) is a histogram where the frequency is the number of 5-digit ZIP codes with a specific YTM. This panel shows that the distribution of average yield-to-maturities is left skewed (as expected for bonds) and has a mode slightly above 5%. Panel (b) shows that the distribution of standard deviations has a long right tail.

Portfolio Optimization We perform portfolio optimization for five different cases: (i) a portfolio that allocates dollars across the ZIP codes of the Western states from California to Washington, and including Oregon, Indiana, Montana, Wyoming, Nevada, Utah, Colorado, Arizona, and New Mexico; (ii) a portfolio for the ZIP codes of the Los Angeles-Long Beach-Anaheim MSA; (iii) San Diego MSA; (iv) Seattle–Tacoma–Bellevue MSA; and (v) San Francisco–Oakland–Fremont MSA.

We simulate yield-to-maturities across 20 simulations of interest rate paths (both risk free rate and 30-year FRM) and spatially correlated wildfires. We then solve for the mean-variance optimizing portfolio with different levels of risk aversion ρ and regularization ξ. Panel (c) of Figure 12 display the allocation of dollars by wildfire propensity score in the case including all Western states, for a risk aversion $\rho = 5$ and a regularization $\xi = 5$. Table B tests the sensitivity of these findings to different values of risk aversion and regularization. Figures 13–14 (a)–(b) plot maps for the allocations of dollars in Los Angeles, San Francisco, Seattle, and San Diego; with the same risk aversion and regularization parameters.

[Figure 12 about here.]

Panel (c) shows that the optimal portfolio has non trivial exposures to wildfire risk. The vertical axis shows the dollar allocation for a 100 million dollar deal. While the ZIP code with the highest dollar allocation has no wildfire exposure, other ZIP codes include areas with substantial wildfire propensity score, up to 0.3% monthly. Table B quantifies this by showing that, for the optimal portfolio, areas with a wildfire propensity score above 0.1% should have a dollar exposure between 38 and 40 million USD.

Figure 13 panel (a) presents the map of dollar allocations for Los Angeles, suggesting allocations between \$500,000 and \$10M per ZIP for a \$100M deal. Areas of the Southeastern part of the MSA (less exposed to wildfires) tend to have the highest dollar allocation, but beyond this fact, the optimal portfolio allocations depend both on historical baseline hazard rates and on wildfire exposure. The optimal portfolio does not include ZIP codes in the Pacific Palisades, location of the most recent wildfire.

[Figure 13 about here.]

Figure 13 panel (b) presents a similar map for San Francisco, where the highest optimal dollar allocations are for the city of San Francisco, Oakland, and Fremont, which have low or moderate fire risk in most locations; and the lowest (non-zero) dollar allocations are for Miramar, Half Moon Bay on the Pacific side, and for San Rafael. The city of San Rafael has some the highest wildfire propensity scores in the Bay area.

Finally, Figure 14 presents the maps for Seattle and San Diego. Some of the highest dollar allocations are in the city of Seattle, and the lowest allocations in the wildfire-prone areas north of Enumclaw and south of North Bend. In San Diego, the highest dollar allocations are in the urbanized areas of the coast, and the lowest allocations in locations further East that are exposed to wildfire risk. The optimization algorithm trades-off wildfire risk, prepayment risk, and foreclosure risk.

[Figure 14 about here.]

This benefit of pooling mortgages across locations arises as the returns are imperfectly correlated. Appendix Figure D, panels (a) and (b) plot the correlation matrix of yield-to-maturities for the ZIP codes of our sample, in the case of the Western States (panel (a)) and for Los Angeles (panel (b)). The covariance matrix is used in the mean-variance optimization 14 exercise. Each row and each column is a ZIP code, and the colors correspond to the correlations $\text{cor}(\tilde{R}_{j0}, \tilde{R}_{j'0})$ for any pair j, j' of ZIP codes. It shows that, while some pairs have highly correlated returns due to prepayment probabilities driven by macroeconomic shocks (Chernov et al. 2018), other pairs have lower correlations due to either different responses of hazard rates to interest rates; or due to different correlations in wildfire occurrence. The standard deviation of deal-level returns can be lowered by pooling such ZIPs. This correlation matrix is, up to the product by diagonal matrices, the covariance matrix Σ of a standard Markowitz (1991) portfolio optimization exercise.

Summarizing Results using Koijen & Yogo (2019) Portfolio Weights Denoting by $w_{j,0}$ the weight of location j in the deal at origination $t = 0$, the log weight can be expressed as a function of the wildfire propensity score and a vector of covariates for the location:

$$\frac{w_{j,0}}{w_{0,0}} = \exp\left(\omega^{w}\text{Wildfire PS}_j + \mathbf{x}_j\boldsymbol{\omega}\right)\varepsilon_{j,0} \tag{31}$$

This is akin to a McFadden (1974) discrete choice model. The portfolio coefficient ω^w measures how the dollar allocation depends on the wildfire propensity score. $\mathbf{x}_j$ is a vector of covariates that MBS sponsors may use when choosing the spatial allocation of dollars. This includes borrowers' FICO scores, income, house values, but may also include the characteristics of the mortgages such as LTV, interest rate, and amortization structure.

Table C presents the coefficients of such analysis, where we pool the weights of the five portfolios: western states, Los Angeles, San Francisco, Seattle, San Diego. The upper panel suggests that the optimal portfolio focuses on areas with lower propensity scores, higher home values, lower household income, and higher FICO scores.

5.7 Adapting to Wildfire Risk in 2050

We can use the tools we develop to assess whether the ability to design the spatial diversification of mortgage-backed securities helps in mitigating the impact of rising wildfire risk in the 21st century. We (i) estimate the change in the wildfire propensity score using IPCC models, (ii) estimate the impact of such rising wildfire propensity score on mortgage performance: ZIP-level yield-to-maturity and the impact on the performance of existing pools, (iii) re-optimize portfolios to account for the rising risk.

IPCC Temperature Projections The first step is to collect data from the IPCC's Coupled Model Intercomparison Projects (CMIP6) models, developed for the Sixth Assessment Report (AR6). The evolution of such temperatures is depicted on Figure 15, where the data includes both in-sample model predictions and out-of-sample predictions. We use the in-sample CMIP6 model predictions of global temperatures and the observed 800-meter PRISM temperature data to estimate the ZIP-level correlation between global temperatures and local ZIP-level temperatures.

We then use the CMIP6 global temperature predictions in 2050 to predict ZIP-level temperatures using the previously estimated correlations. Then, in combination with the coefficients of the wildfire propensity model estimated on Table 2, we forecast wildfire risk at the 5-digit ZIP code level in 2050 holding other parameters constant, including electric lines, land cover, and the road network. Other parameters could evolve over the time period 2022-2050 and 2050-2100. This paper focuses on one dimension of such Lucas critique, the evolution of MBS pooling; and keeps other parameters constant.

[Figure 15 about here.]

Figure 16 presents a map of the coterminous US with the average wildfire propensity score in-sample, from 2010 to 2021 (upper panel), and, the evolution of the wildfire probabilities by 5-digit ZIP codes (lower panel). Areas in the periphery of the metropolitan areas of Los Angeles, San Francisco, Seattle experience large increases in wildfire probabilities, consistent with the finding that wildfire risk is highest at the urban-wildland interface (Kestelman 2023). Other areas with substantial increases in wildfire probabilities include Southeast Florida.

[Figure 16 about here.]

Using these forecasts, we can then simulate the cash flows by month, for 360 months, for each of the numerical simulations. The probability of wildfires increases in most locations. We keep the spatial correlation of wildfire probabilities constant. We keep the 20 interest rate simulations constant and only incorporate what, in the prepayment and foreclosure hazard rates, is due to the increased risk of wildfires. We then calculate the impact of such 2050 risk on the yield-to-maturities of each ZIP code and compute the optimal portfolio allocation across 5-digit ZIP codes.

[Figure 17 about here.]

The first finding is that the increased wildfire activity has an economically significant impact on the average and standard deviation of ZIP-level yield-to-maturity as presented on panels (a) and (b) of Figure 17. The lower tail of yield-to-maturities experiences some of the largest declines in performance. Virtually all ZIP codes experience a decline in average yield-to-maturity and an increase in the standard deviation of YTMs. For most ZIP codes the increase in standard deviation is between 0 and 1 percentage point. Yet, as will see below, the optimal portfolio is mostly resilient to the rise in wildfire risk.

Panel (c) suggests that the optimal portfolio with 2050 wildfire risk has lower dollar allocations in a number of specific areas; which, as the maps of Figures 13 and 14 will show, are exposed to wildfire risk. Panels (c) and (d) of Figures 13 and 14 present the ZIP-level change in dollar allocation between the portfolio with current risk and the portfolio with 2050 wildfire risk. In the case of San Francisco, Seattle, and San Diego, the largest declines in portfolio allocation are experienced in wildfire-prone areas. This is not true of the optimal portfolio in some part of Los Angeles, where there is a trade-off: changes in wildfire risk are offset by the still lower baseline prepayment and foreclosure rates, mitigating the attractiveness of locations with lower wildfire risk.

Table C, lower panel, presents the new Koijen & Yogo (2019) portfolio coefficients when using 2050 deal-level optimal weights. The coefficient on the wildfire propensity score is 2 to 3 times higher (columns (1) to (5)) than the coefficient for the optimal deal with current risk. The importance of income increases moderately, but overall the other covariates (income, house value, fico) have a similar impact with current and with 2050 wildfire risks.

5.8 Portfolios' Resilience to 2050 Climate Risk

Figure 12, panels (a) and (b) suggest that ZIP codes have very different returns, ranging from below -5% to above 5% annually. The standard deviation of returns is also highly variable across ZIP codes, with risk ranging from almost risk-free to above 3%.

Figure 17 also suggests that specific ZIP codes are strongly affected by rising wildfire risk. When simulating the impact of 2050 wildfire risk on returns (yield-to-maturity) we observe impacts of up to 5 percentage points in expectation, and more than a 1 percentage point of standard deviation.

[Figure 18 about here.]

Figure 18 shows that portfolios other than the mean-variance-maximizing portfolio tend to be affected by wildfire risk. These results are obtained by simulating 1,000 portfolios using Koijen & Yogo (2019) coefficients drawn randomly with a normal distribution. This generates a range of possible portfolios with different return, risk, and wildfire profiles. Subfigure (c) suggests impacts of 2050 wildfire risk of up to 15% for some portfolios, with a long left tail and a mass around a zero impact of wildfire risk. Subfigure (d) shows impacts of wildfire risk between 0 and 2.5 ppt, with a long right thick tail with impacts reaching standard deviations above 7.5 ppt. This is consistent with Subfigure (e): the Koijen & Yogo (2019) coefficient of the wildfire propensity score is negatively correlated with the expected return (yield-to-maturity). Overall, panels (a)–(f) suggest that there is a tail of portfolios that are exposed to wildfire risk.

Yet, the optimal portfolio that was found by solving the mean-variance optimization program is resilient to rising wildfire risk, even as it is exposed to non-zero wildfire propensity (Appendix Table B). Figure 17 panel (d) suggests that the optimal portfolio in 2050 is less exposed to wildfire risk.

To see this decompose the impact of 2050 risk into two separate terms: (i) the raw impact, at given pooling, and (ii) the benefit of repooling the Mortgage-Backed Security. Denote by $\tilde{\mathrm{R}}(\mathbf{w}_0, \mathrm{PS})$ the return of the Mortgage-Backed Security obtained with the vector of weights $\mathbf{w}_0$ and with the vector of wildfire propensity scores PS. The impact of rising wildfire risk is:

$$\begin{aligned} & \mathbb{E}(\tilde{\mathbf{R}}(\mathbf{w}_0^{2050}, \mathrm{PS}^{2050})) - \mathbb{E}(\tilde{\mathbf{R}}(\mathbf{w}_0, \mathrm{PS})) \\ = \; & \underbrace{\mathbb{E}(\tilde{\mathbf{R}}(\mathbf{w}_0^{2050}, \mathrm{PS}^{2050})) - \mathbb{E}(\tilde{\mathbf{R}}(\mathbf{w}_0, \mathrm{PS}^{2050}))}_{\text{Impact of New Optimal Spatial Diversification}} + \underbrace{\mathbb{E}(\tilde{\mathbf{R}}(\mathbf{w}_0, \mathrm{PS}^{2050})) - \mathbb{E}(\tilde{\mathbf{R}}(\mathbf{w}_0, \mathrm{PS}))}_{\text{Direct Impact of Rising Risk}} \end{aligned} \tag{32}$$

The numerical analysis performed in the data archive estimates the magnitude of these two effects for the optimal portfolio. At the optimal portfolio, the direct impact (second term) of rising wildfire risk is approximately -35 basis points (35.47) annually. The benefit of repooling (first term) is approximately $+21$ basis points (21.03) annually. Overall, the net impact of rising risk is approximately 14 basis points (14.44).

6 Discussion

6.1 Pools of pools

The transactions costs of mortgage origination and MBS sponsoring are typically larger than the transaction costs of building portfolios of deals. This section presents the mechanics of building pools of pools using the method described in this paper, by nesting portfolio choice at the MSA-level into a nationwide pool of pools. A key element in this analysis is the spatial correlation of risk between MSA-level pools. This spatial correlation of returns across different MBSs is due to the (a) common sensitivity of prepayment and foreclosure hazard rates to interest rates, which are macroeconomic factors (Chernov et al. 2018) and due to the (b) rising nationwide spatial correlations in wildfire risk, presented on Figure 4.

We present a numerical implementation of such approach, in the case of pools spanning each a single MSA.[24]

The mean-variance optimization optimization can be performed by block (below, each block is a single MSA), such that: $\mathbf{w}_0 = (\mathbf{w}_1, \mathbf{w}_2)$. The allocation of weights spans two areas, with each J_1 and J_2 locations respectively. In this case the optimal portfolio problem can be written as the nested optimization of two deals, accounting for the correlation between the returns of the two deals.[25] To see this, let's write the overall optimization problem:

$$\max_{\mathbf{w}_1,\mathbf{w}_2} \quad \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \end{bmatrix}' \boldsymbol{\mu}_1 - \frac{1}{2}\rho \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \end{bmatrix}' \begin{bmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{12} & \boldsymbol{\Sigma}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \end{bmatrix} - \xi \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \end{bmatrix}' \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \end{bmatrix} \tag{33}$$

$$\text{s.t.} \quad \mathbf{w}_1'\mathbf{1}_{J_1} + \mathbf{w}_2'\mathbf{1}_{J_2} = 1 \tag{34}$$

$$\text{s.t.} \quad w_{j_1 1}, w_{j_2 2} \geq 0 \qquad \forall j_1, j_2 \tag{35}$$

and write the subproblem of finding each vector of weights, accounting for (i) the share of the fund of deals allocated to each deal $k = 1, 2$, denoted s_k, with $s_1 + s_2 = 1$ and (ii) the correlation with the other parts of the portfolio.

For each deal $k = 1, 2$:

$$\max_{\mathbf{w}_k} \quad \mathbf{w}_k'\boldsymbol{\mu} - \frac{1}{2}\rho \mathbf{w}_k' \boldsymbol{\Sigma}_{\boldsymbol{kk}} \mathbf{w}_k - \xi \mathbf{w}_k' \mathbf{w}_k \tag{36}$$

$$\text{s.t.} \quad \mathbf{w}_k'\mathbf{1} = s_k \tag{37}$$

$$\text{s.t.} \quad w_{jk} \geq 0, j = 1, 2, \ldots, J_k \tag{38}$$

$$\text{s.t.} \quad \mathbf{w}_1' \Sigma_{12} \mathbf{w}_2 = \varphi \tag{39}$$

Condition (37) expresses that share of deal k in the overall portfolio is s_k. Condition (39) expresses

[24] We thank Johannes Stroebel for this suggestion.

[25] In this sense a similar issue arises when considering multistrategy funds and funds of funds (Reddy, Brady & Patel 2007, Gao, Haight & Yin 2020).

that the covariance between deals 1 and 2 is φ. This is thus a question of finding allocations $\mathbf{w}_1, \mathbf{w}_2$, shares allocated in each portfolio $s_1, s_2 = 1 - s_1$, and the covariance between deals φ. Given the covariance constraint (39) between the returns of the deals, this optimization will be typically different than the selection of optimal deals separately by MSA, performed on Figure 13 following (14) in Section 5.1.

The optimal pool's statistics when considering all ZIP codes in western states are presented on Figures 12 and 17, panels (c) and (d). The MSA-level pools are presented on Figures 13 and 14. Table C of Koijen & Yogo (2019) portfolio coefficients considers both these MSA-level and the pool for western states in a single regression.

6.2 Multiple Risks

This paper's approach can accommodate a variety of risk factors, including non-climate related risks such as unemployment, and other climate-related risks such as precipitation events and hurricane storm surges. This is done by adding exogenous shocks to the hazard rate specifications (23), (24), and by drawing realizations of these shocks accounting for their spatial correlation (e.g. the spatial correlation in shocks to local sectoral activity). The portfolio optimization approach (14) solves the allocation problem without constraining the variance-covariance to a specific number of factors.

Hall & Maingi (2021) and Rendon & Bazer (2021) estimate the impact of unemployment on prepayment and default. Davidson & Levin (2014) provides evidence on the importance of the different risk factors. Addoum et al. (2023) estimates the impact of hurricane Sandy on the performance of commercial mortgages. Gete et al. (2020) estimates the impact of hurricanes on the performance of mortgages in Credit Risk Transfers (CRT) pools. The methods of this paper can thus be extended to a larger number of risk factors.

6.3 The Stability of Treatment Effects

The 2050 simulations focus on a single margin of climate change adaptation: the ability to design mortgage-backed securities by changing the spatial selection of mortgages. The probability of wildfires evolves, while keeping the dynamic of interest rates and the treatment effect of wildfires on prepayment and foreclosure rates constant.

Other margins of climate change adaptation may be relevant for the ability of the MBS market to adapt to 2050 wildfire risk. First, the event study sections of this paper suggest that wildfires cause changes in LTV (higher downpayment) and interest rate (pricing of risk). Second, the impact of wildfires on prepayment and foreclosure rates could evolve by 2050. Wildfires could have higher or lower impacts on prepayment and foreclosure rates, depending on households' ability to adapt to risk. Wildfire could cause lower prepayment and foreclosure rates if, e.g. households adapt by fireproofing their homes (Standohar-Alfano, Estes, Johnston, Morrison & Brown-Giammanco 2017), or by relocating to safer locations (McConnell, Fussell, DeWaard, Whitaker, Curtis, St. Denis, Balch & Price 2024). Building codes may also evolve (McFarlane, Li & Hollar 2021).

7 Conclusion

With rising climate risk involving significant parts of the financial system (Coronese, Lamperti, Keller, Chiaromonte & Roventini 2019, Monasterolo 2020), the returns to better financial engineering increase. New sources of systematic risk, such as wildfire risk, generate demand for a complete market of securities with heterogeneous disaster risk exposures. This includes Mortgage-Backed Securities, Insurance Linked Securities, and Credit Risk Transfers.

This paper provides a constructive path to design such *climate risk efficient frontier* of securities with different returns and wildfire risk exposure as global temperatures rise. Such securities may be designed so that natural disasters have no noticeable impact on deal-level cash flows. Other securities may offer a significant covariance with global temperatures. This paper provides quantifiable metrics that can assess the risk exposure of securities, and *in reverse*, provides tools to bundle cash flows to target a specific risk exposure.

Diversification also enables the financial engineer to smooth out the tail risk of individual locations, preventing large catastrophes that have been the focus of macroeconomics and finance (Barro & Ursúa 2012, Pindyck & Wang 2013); current correlations suggest signification diversification benefits. As local correlations rise, pooling risk beyond state borders makes the financial system more resilient.

Mortgages are light to 'ship to pools' across the United States; in trade, iceberg costs have been an obstacle to international risk sharing (Dingel et al. 2019), and lowering them has welfare benefits (Irarrazabal, Moxnes & Opromolla 2015). The globalization of climate finance provides a larger set of uncorrelated or negatively correlated cash flows that help reduce the tail risk of individual locations.

This paper highlights the importance of correlation metrics rather than the assessment of local probabilities. In the growing market for climate risk assessments, spurred by the SEC's new climate change disclosure rules, investors and regulators alike can acknowledge the benefits of assessing portfolio correlations as those drive risk over and above average risk probabilities.[26]

[26] "The Enhancement and Standardization of Climate-Related Disclosures for Investors", issued March 6, 2024, https://www.sec.gov/rules/2022/03/enhancement-and-standardization-climate-related-disclosures-investors.

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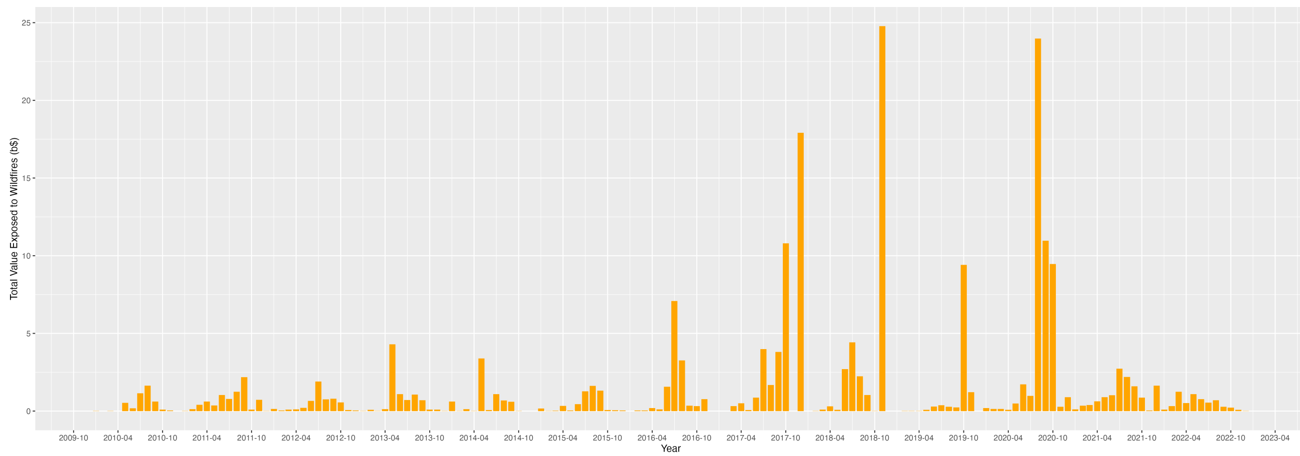
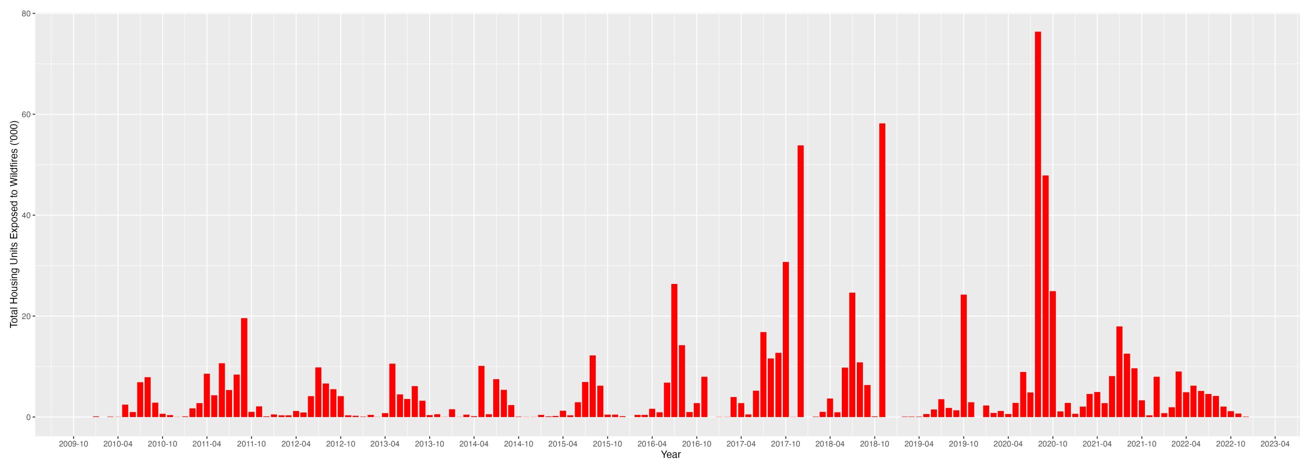
Figure 3: Rising Wildfire Frequency – Surface Area of Wildfire Perimeters, Housing Units and Total House Value Affected

These three charts present the annual exposure to wildfires by (a) housing value, (b) the number of housing units, (c) surface area. The surface area exposed is in square kilometers. The number of housing units exposed is the sum of housing units at the Census tract level within wildfire perimeters. Housing values from the 2010 Census.

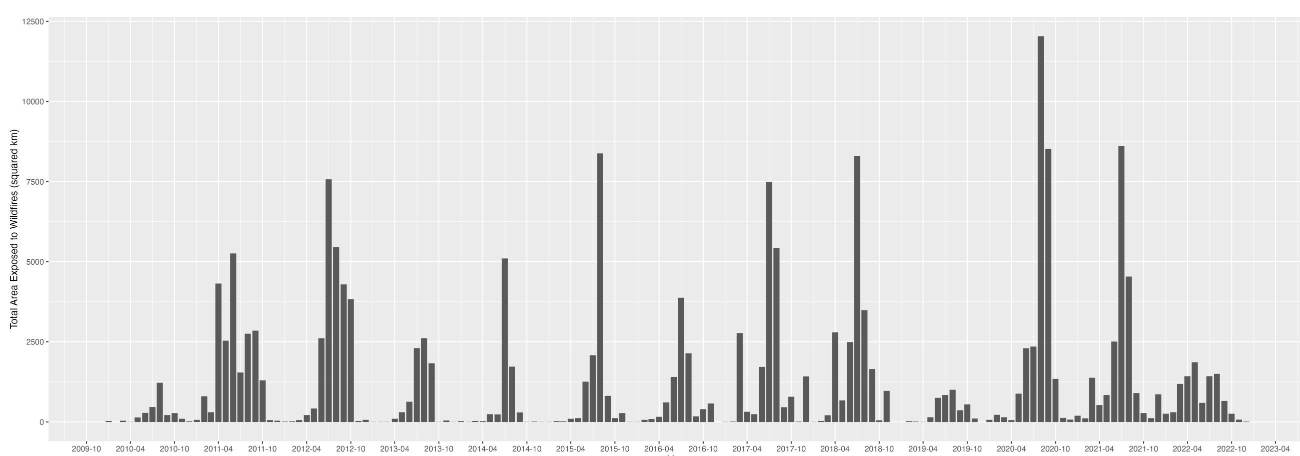
(a) Housing Value Exposed



(b) Housing Units Exposed



(c) Surface Area Exposed

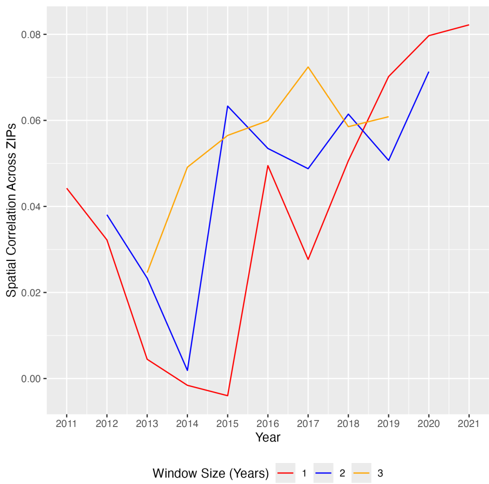


Sources: Wildfire perimeters from GeoMAC, NIFC. Census aggregate house values.
Area, ZCTA5 boundaries, US National Atlas projection.

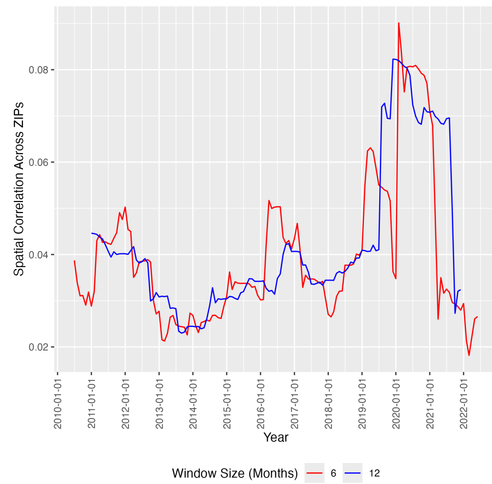
Figure 4: Spatial Correlations in Wildfire Risk – Annual and Monthly Frequency

These figures show the evolution of the spatial correlation in wildfire occurrence across ZIP codes, using 1,2, or 3 year time windows (left column), or using a 6 or 12 month time window (right column). Panels (a) and (b) weigh the ZIP codes by housing units. Panels (c) and (d) weigh the ZIP codes by aggregate housing value. Panels (e) and (f) weigh by area affected. The spatial correlation is obtained by regressing the wildfire indicator on the average wildfire indicators of other ZIPs in the same time window.

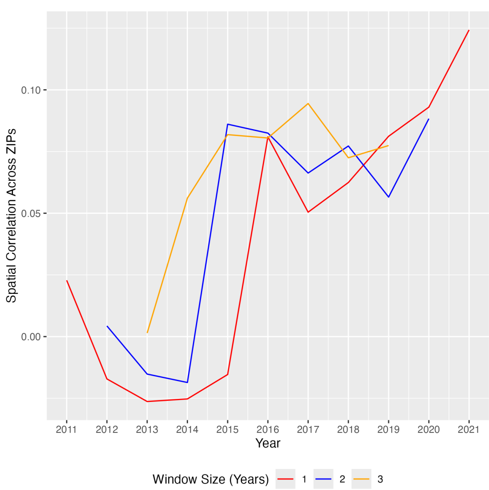
(a) Weighted by Housing Units Affected



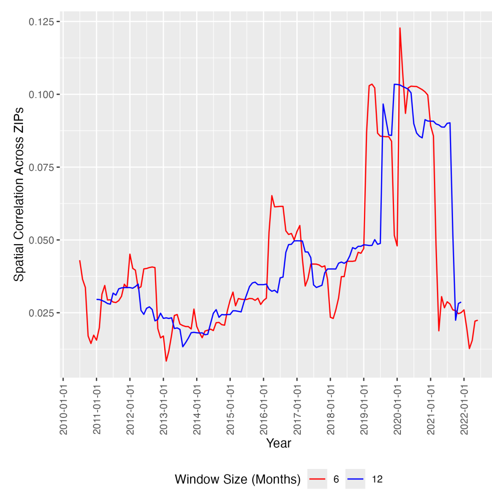
(b) Same Weighting, Monthly



(c) Weighted by Value of Housing Units Affected



(d) Same Weighting, Monthly



(e) Weighted by Area Affected

(f) Same Weighting, Monthly

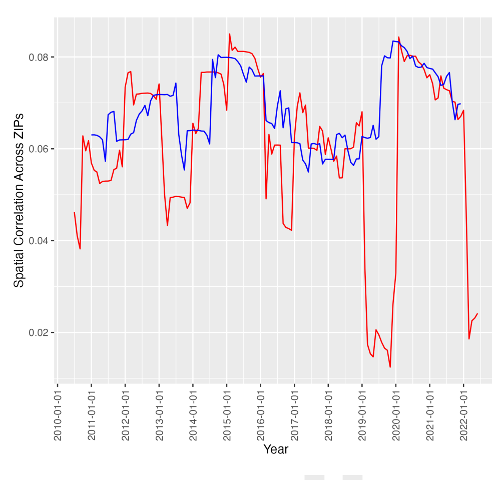


Figure 5: Mortgage-Level Analysis – Wildfire Exposure and Incremental Foreclosure Probability

The figures present the two-way DiD regression of the likelihood of foreclosure using equation (2). We obtain propensity scores (PS3) from regression (4) of Table 2. Propensity-score-weighted, robust standard errors are clustered by mortgage. The 95% confidence intervals are presented for the event study from −9 months and +12 months around a wildfire event.

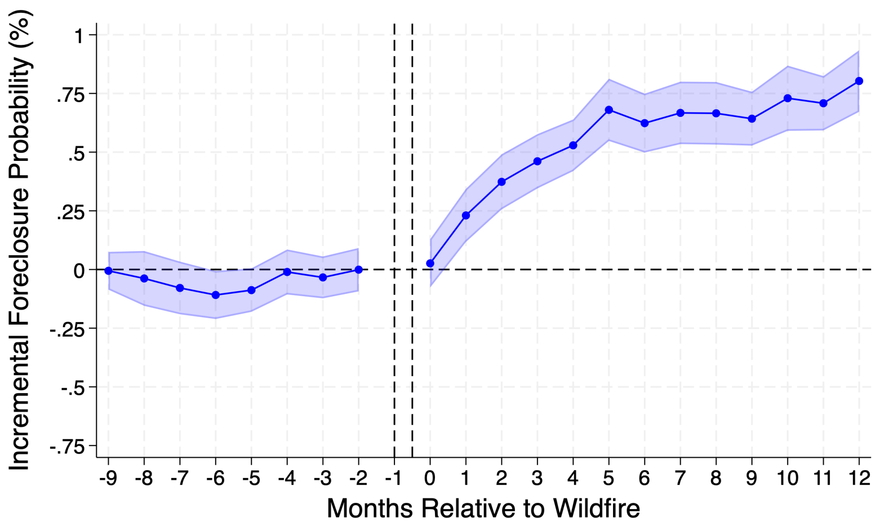


Figure 6: Mortgage-Level Analysis – Wildfire Exposure and Incremental Prepayment Probability

The figures present the two-way DiD regression of the likelihood of prepayment using equation (2). We obtain propensity scores (PS3) from regression (4) of Table 2. Propensity-score-weighted, robust standard errors are clustered by mortgage. The 95% confidence intervals are presented for the event study from −9 months and +12 months around a wildfire event.

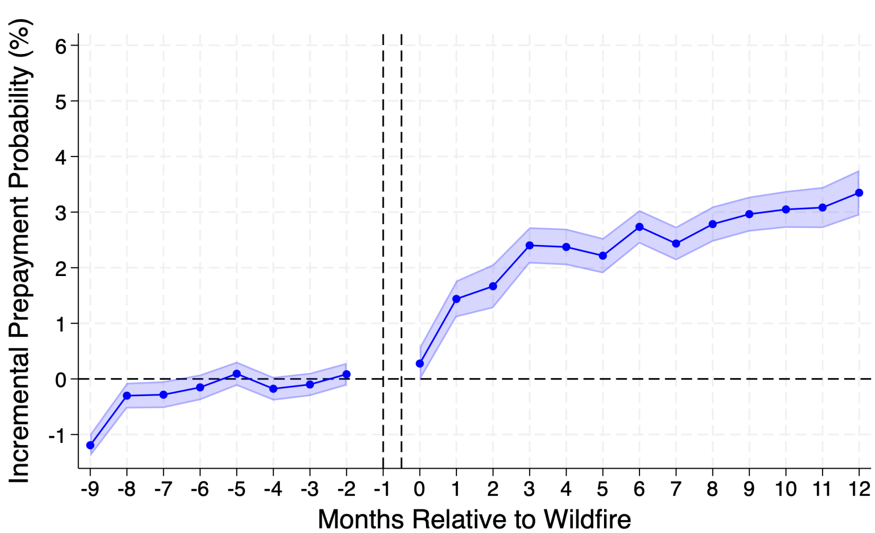
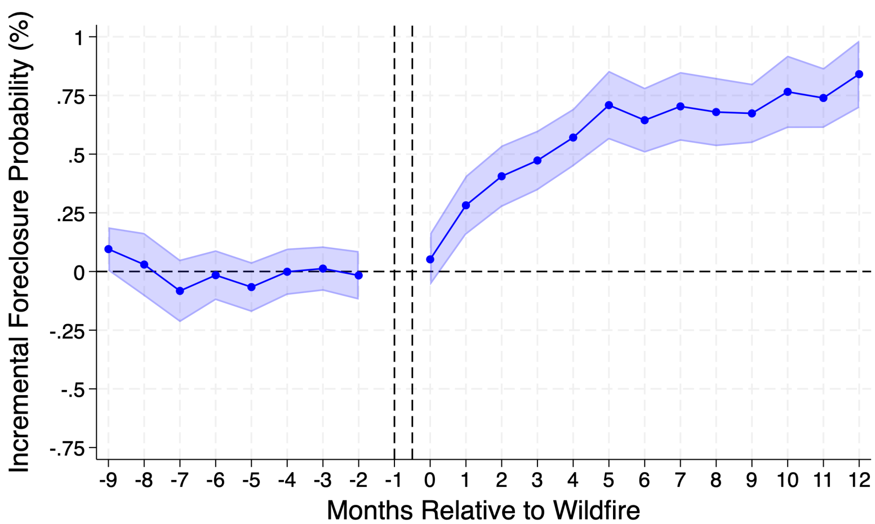


Figure 7: Mortgage-Level Analysis – Wildfire Exposure and Incremental Foreclosure by Location

The figures present the two-way DiD regression of the likelihood of foreclosure by California and rest of the US using equation (2). We limit our sample to mortgages in California in panel (a), and the mortgages in the rest of the US in panel (b). We obtain propensity scores (PS3) from regression (4) of Table 2. Propensity-score-weighted, robust standard errors are clustered by mortgage. The 95% confidence intervals are presented for the event study from -9 *months and* $+12$ *months around a wildfire event.*

(a) California



(b) Rest of the US

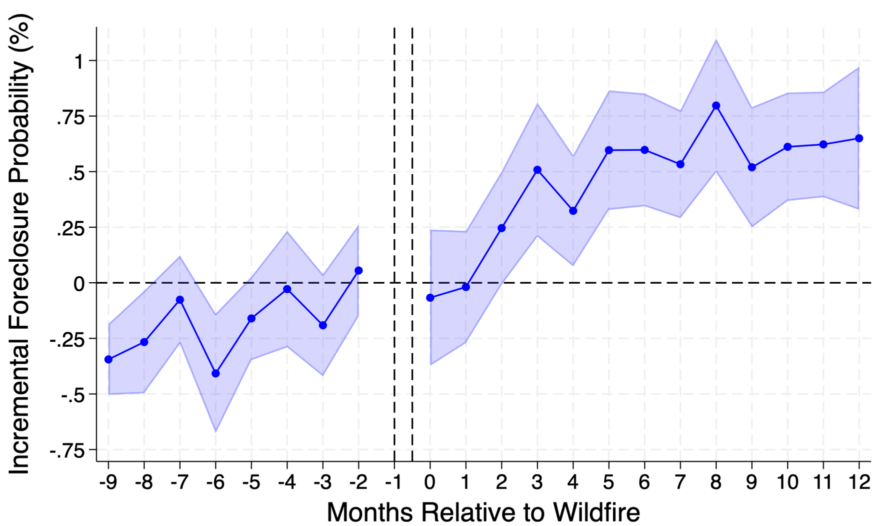
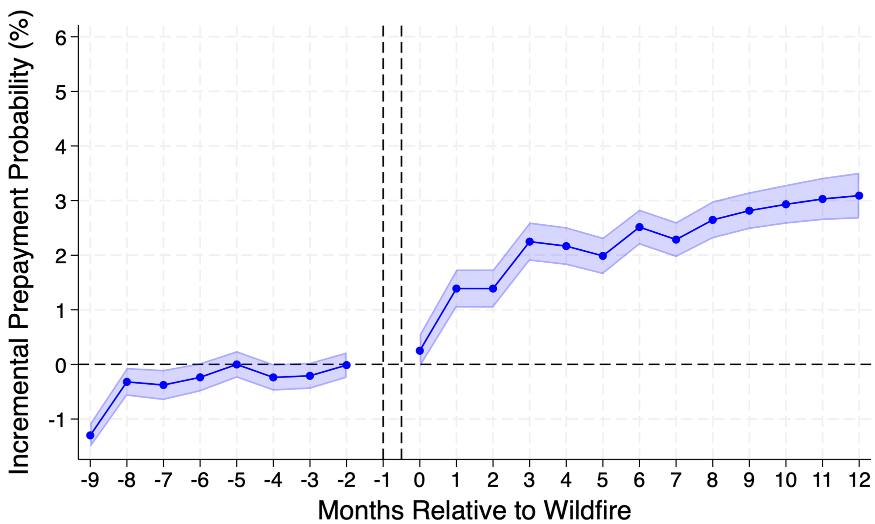


Figure 8: Mortgage-Level Analysis – Wildfire Exposure and Incremental Prepayment by Location

The figures present the two-way DiD regression of the likelihood of prepayment by California and rest of the US using equation (2). We limit our sample to mortgages in California in panel (a), and the mortgages in the rest of the US in panel (b). We obtain propensity scores (PS3) from regression (4) of Table 2. Propensity-score-weighted, robust standard errors are clustered by mortgage. The 95% confidence intervals are presented for the event study from −9 months and +12 months around a wildfire event.

(a) California



(b) Rest of the US

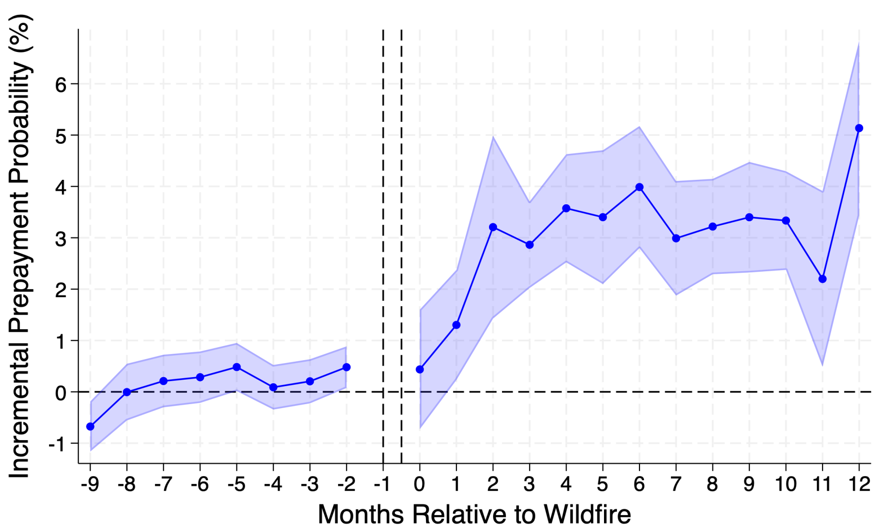
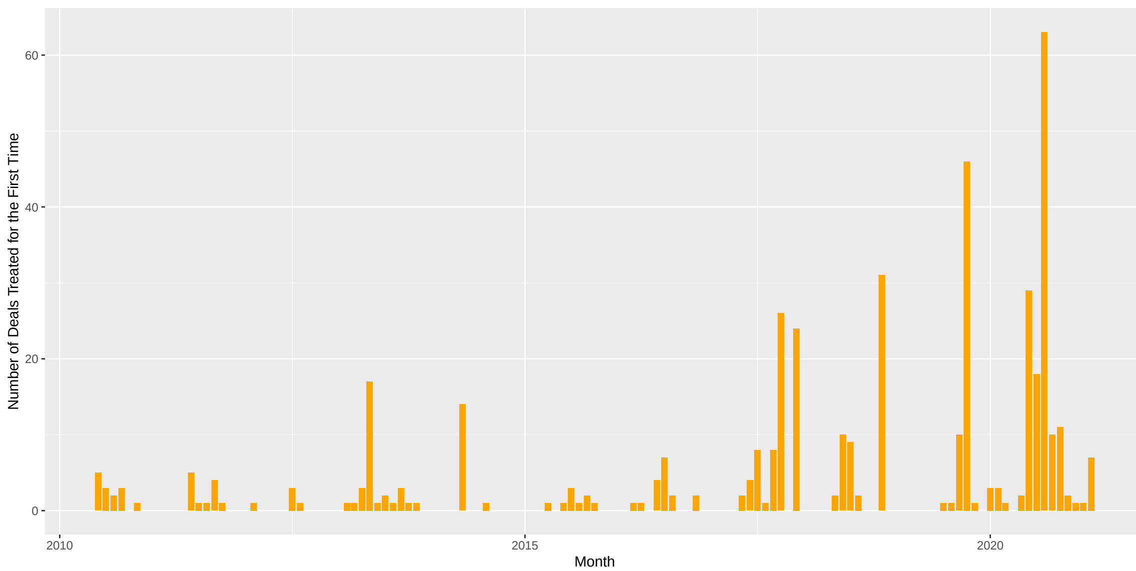


Figure 9: MBS Deal Analysis – The Exposure of MBS to Wildfires – Event Study Design

The upper panel presents, across months, the number of MBS deals in the treatment group. A deal is in the treatment group when the treated ZIP codes represent more than 5% of the unpaid principal balance of the deal. The upper panel is for the first exposure. The lower panel is for subsequent exposures. For each event of the upper panel, we consider a −12 to +24 months time window around the event for the treated MBS deals.

(a) Number of Deals Treated for the First Time



(b) Number of Deals Treated for the Second Time or More

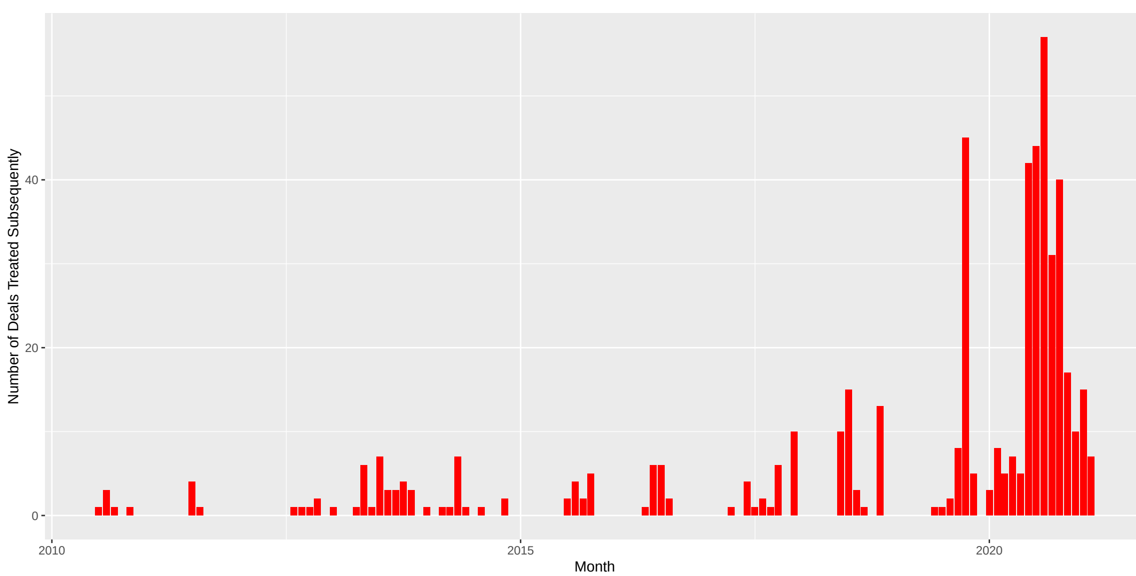
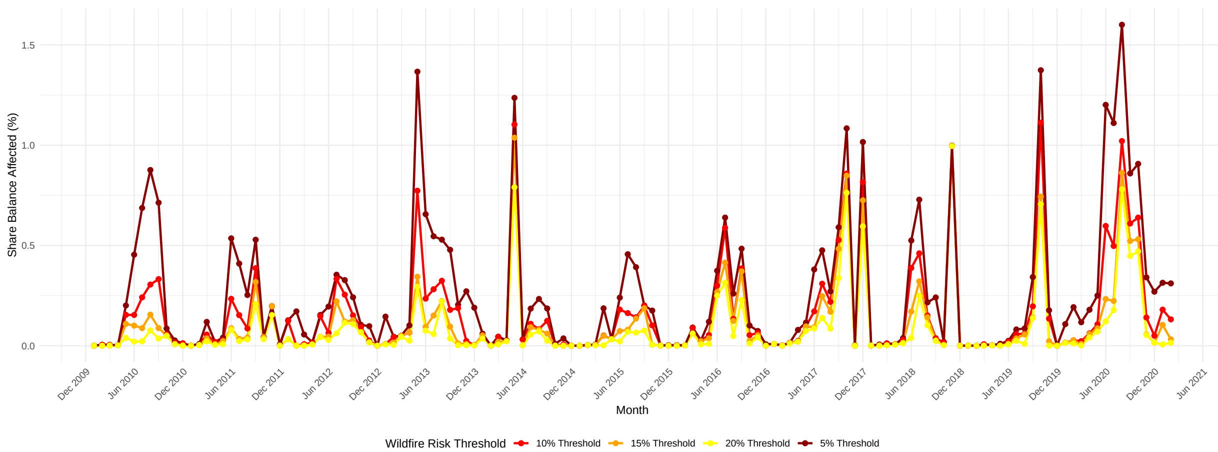


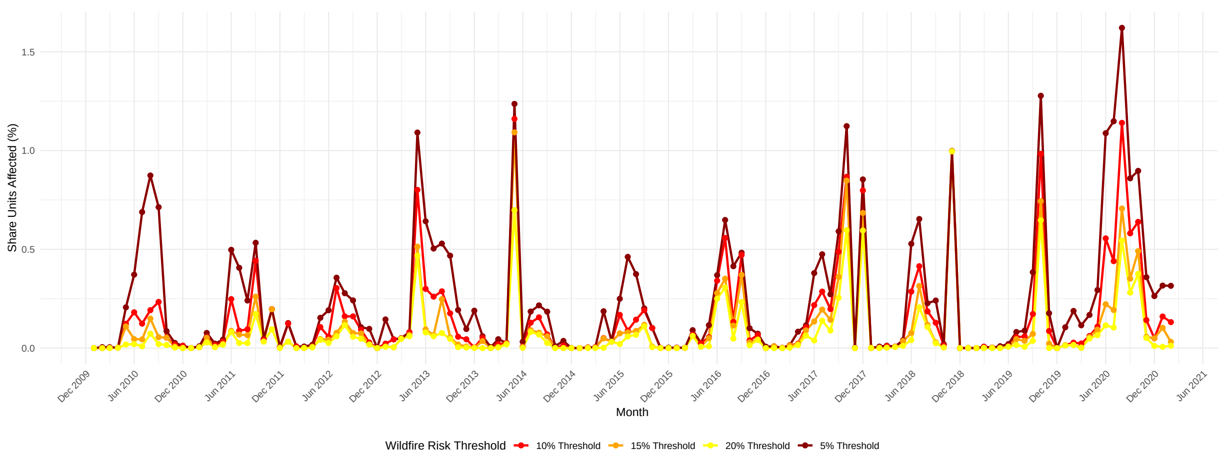
Figure 10: MBS Deal Analysis – The Exposure of MBS to Wildfires – At Different Thresholds

The three panels present, across months, the number of MBS deals exposed by share of the UPB in treated ZIPs. On this figure, a ZIP is treated if the affected area represents more than 5%, 10%, 15%, or 20% of the housing value, measured at the tract level.

(a) Within MBS Deals, Share of Balance Affected



(b) Within MBS Deals, Share of Housing Units Affected



(c) Total Balance Affected (M USD)

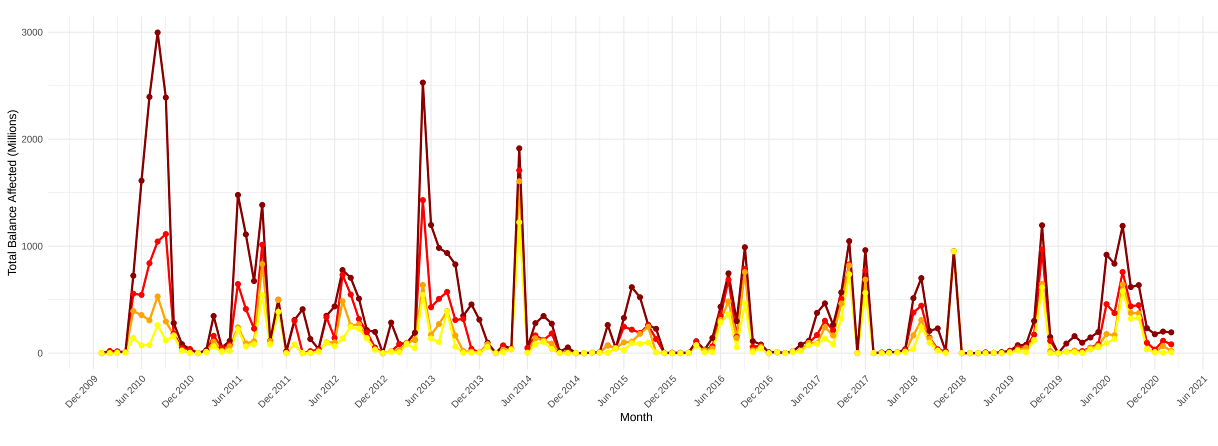
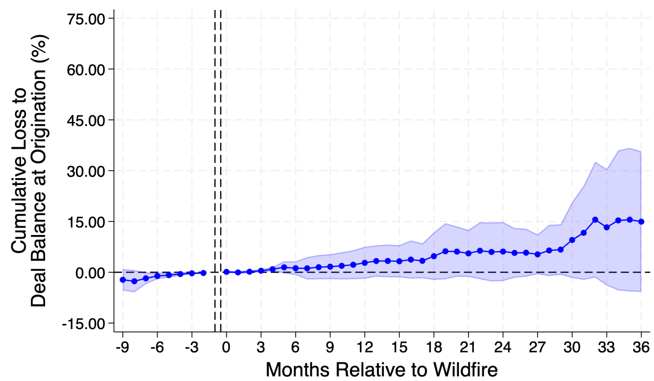


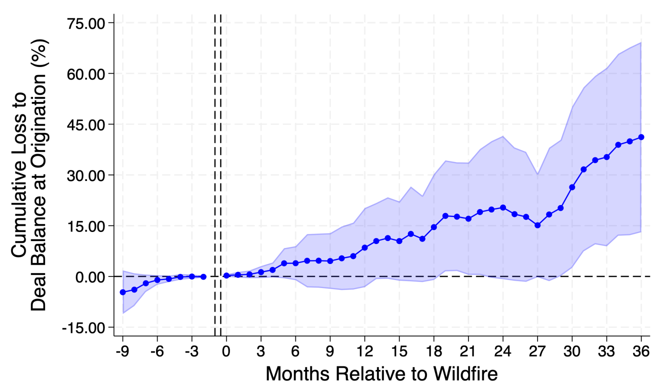
Figure 11: MBS Deal Analysis – Wildfire Exposure and Cumulative Loss of Deals

The figures present the two-way DiD regression of the likelihood of cumulative loss of a deal since its inception using equation (12). The wildfire shock is defined as the month in which one or more fires begin and have the greatest impact on the outstanding balance of a mortgage deal. The treatment group includes deals in which the wildfire shock impacts at least 5% of the deal balance in panel (a), 10% in panel (b), and 15% in panel (c). The control group comprises deals either unaffected by wildfires or with less than 5% of the balance impacted. Individual mortgage characteristics are weighted by outstanding balance at the deal level. We obtain mortgage-level propensity scores (PS3) from regression (4) of Table 2. Then, we calculate propensity scores at the deal level weighting them by outstanding balance. Deal-level propensity-score-weighted, robust standard errors are clustered by mortgage. The 95% confidence intervals are presented for the event study from −9 months and +36 months around a wildfire event.

(a) Deals Affected by at least 5% of Deal Balance



(b) Deals Affected by at least 10% of Deal Balance



(c) Deals Affected by at least 15% of Deal Balance

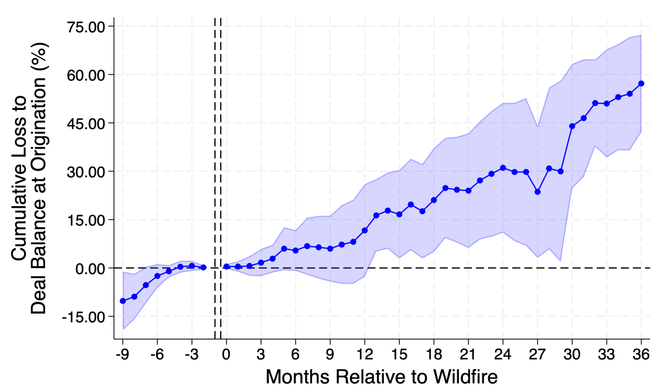
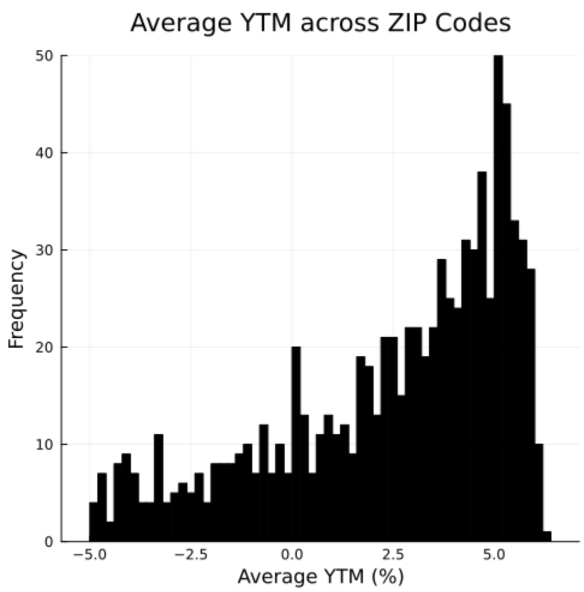


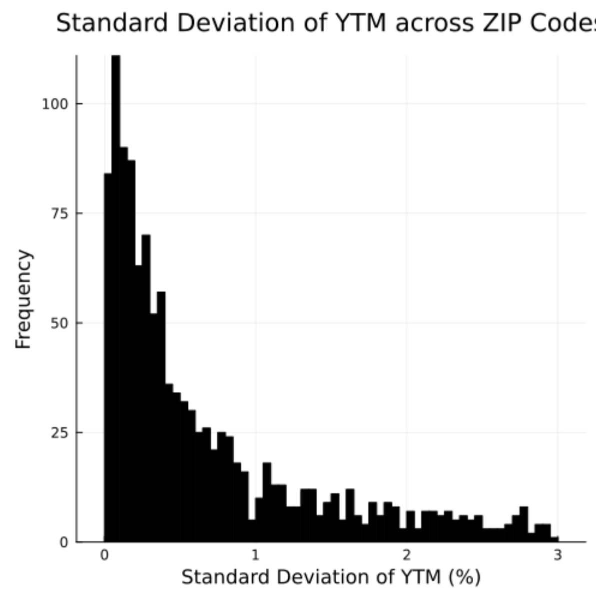
Figure 12: Designing MBSs – Simulated Pools and their Performance

For each allocation $\mathbf{w}_0$ *of origination dollars across the ZIP codes of the sample, we simulate the cash flows of the pool over 360 months and obtain the mean and variance of yield-to-maturities. This allows us to solve for the mean-variance maximizing portfolio (14). The upper panels show the distribution of average and standard deviation of returns, by ZIP, quoted on an annual basis. We do not plot ZIPs in the lower tail, which are unlikely to be part of the optimal portfolio. The lower panels plot the optimal allocation of origination dollars at the mean-variance optimizing MBS, with current risk (panel (c)) and the change in optimal allocation with 2050 wildfire risk. The optimal allocation is obtained with a risk aversion* $\rho = 5.0$ *and a regularization parameter* $\lambda = 5.0$.

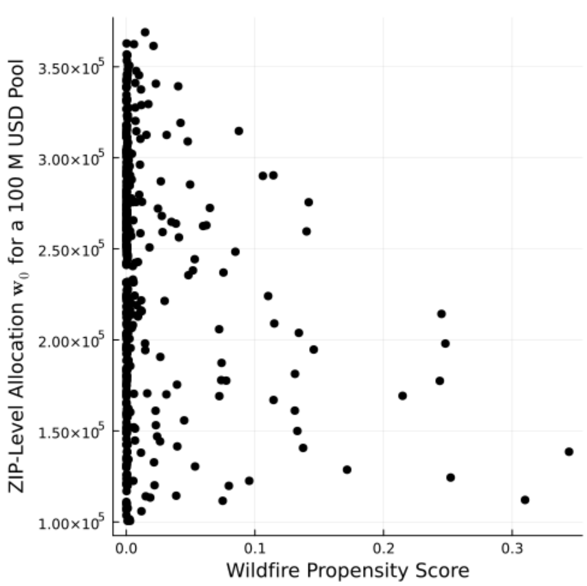
(a) Distribution of Average Returns, ZIP-Level



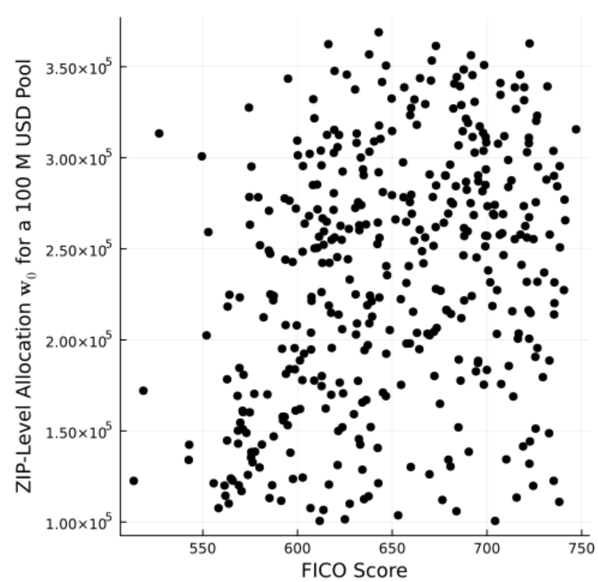
(b) Standard Deviation of Returns, ZIP-Level



(c) Optimal Allocation of Origination Dollars, MBS-Level



(d) Optimal Allocation of Origination Dollars, MBS-Level

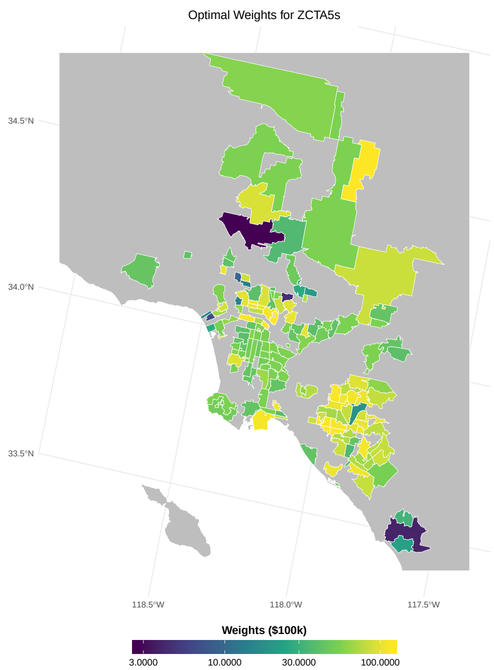


Source: Simulations by the authors. ZIP-level cash flows calculated using the historical ZIP-level prepayment and foreclosure rates and a two-step Heckman approach. Impact of wildfires on hazard rates estimated on Figures 5 and 6. Wildfire frequencies and within-state spatial correlations across ZIP codes estimated using National Fire Interagency data. Code for this optimization in the `src/Pooling/4_optimal_design` *folder of the code repository.*

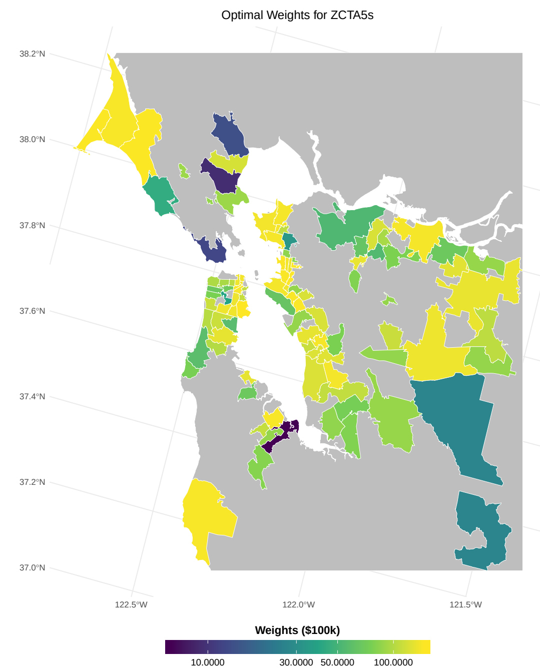
Figure 13: Designing MBSs – Optimal Portfolio and Change in Optimal Weights, Current Risk vs 2050 Risk

The upper panels plot the dollar allocation of mortgage originations of the mean-variance-maximizing portfolio for Los Angeles and San Francisco. The lower panels plot the percentage change in mortgage originations as we perform mean-variance maximization with 2050 wildfire risk.

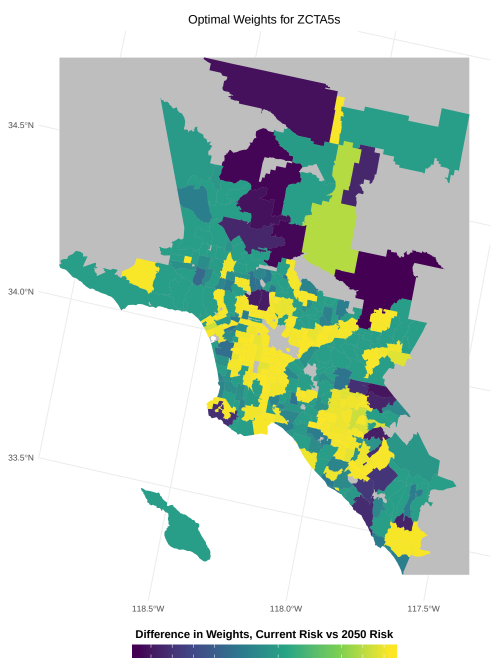
(a) Los Angeles, Optimal Portfolio



(b) San Francisco, Optimal Portfolio



(c) Los Angeles, % Difference in Optimal Weights, now to 2050



(d) San Francisco, % Difference in Optimal Weights, now to 2050

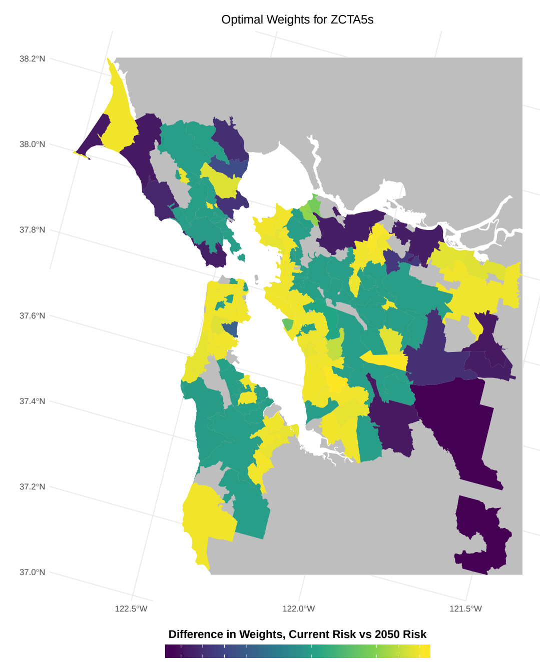
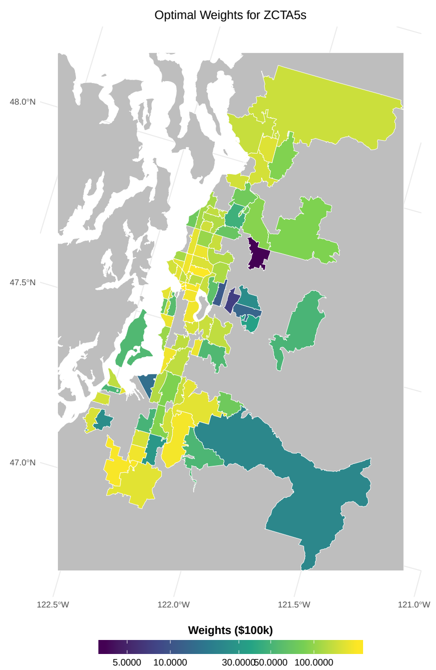


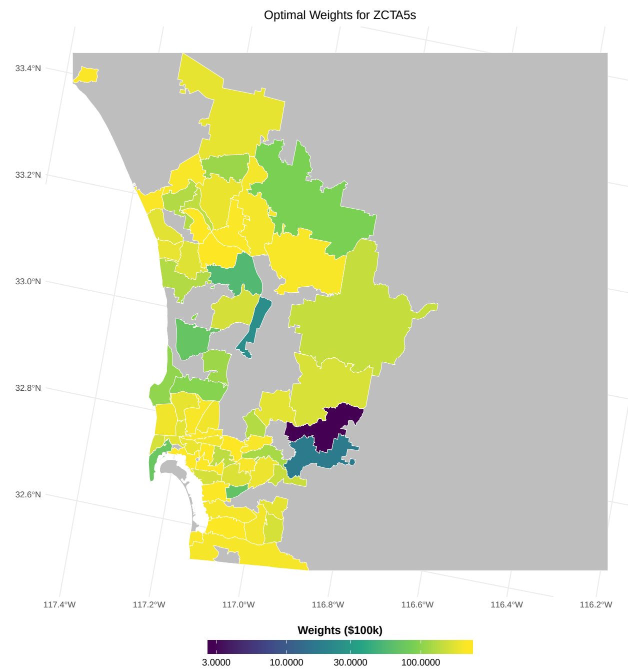
Figure 14: Designing MBSs – Optimal Portfolio and Change in Optimal Weights, Current Risk vs 2050 Risk

The upper panels plot the dollar allocation of mortgage originations of the mean-variance-maximizing portfolio for Seattle and San Diego. The lower panels plot the percentage change in mortgage originations as we perform mean-variance maximization with 2050 wildfire risk.

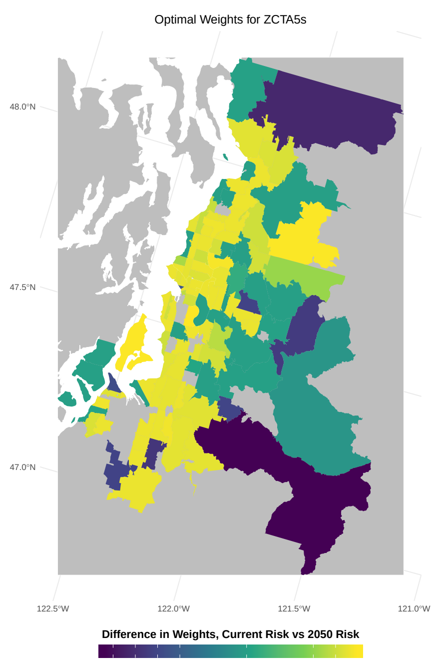
(a) Seattle, Optimal Portfolio



(b) San Diego, Optimal Portfolio



(c) Seattle, % Difference in Optimal Weights, now to 2050



(d) San Diego, % Difference in Optimal Weights, now to 2050

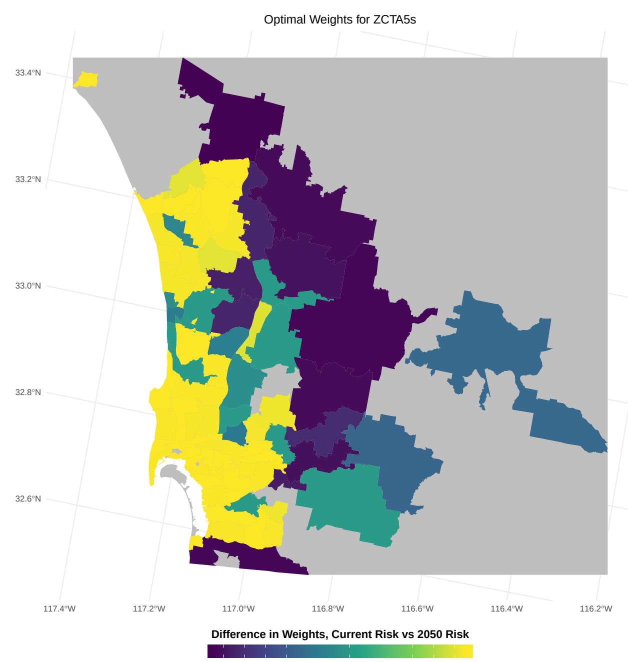


Figure 15: Designing MBS Deals with Evolving Risk – Global Surface Temperature Forecasts

This line chart presents the simulated global surface temperature according to each of the IPCC's CMIP6 models. We average these simulated temperatures across models. CMIP6 models include both in-sample and out-of-sample predictions.

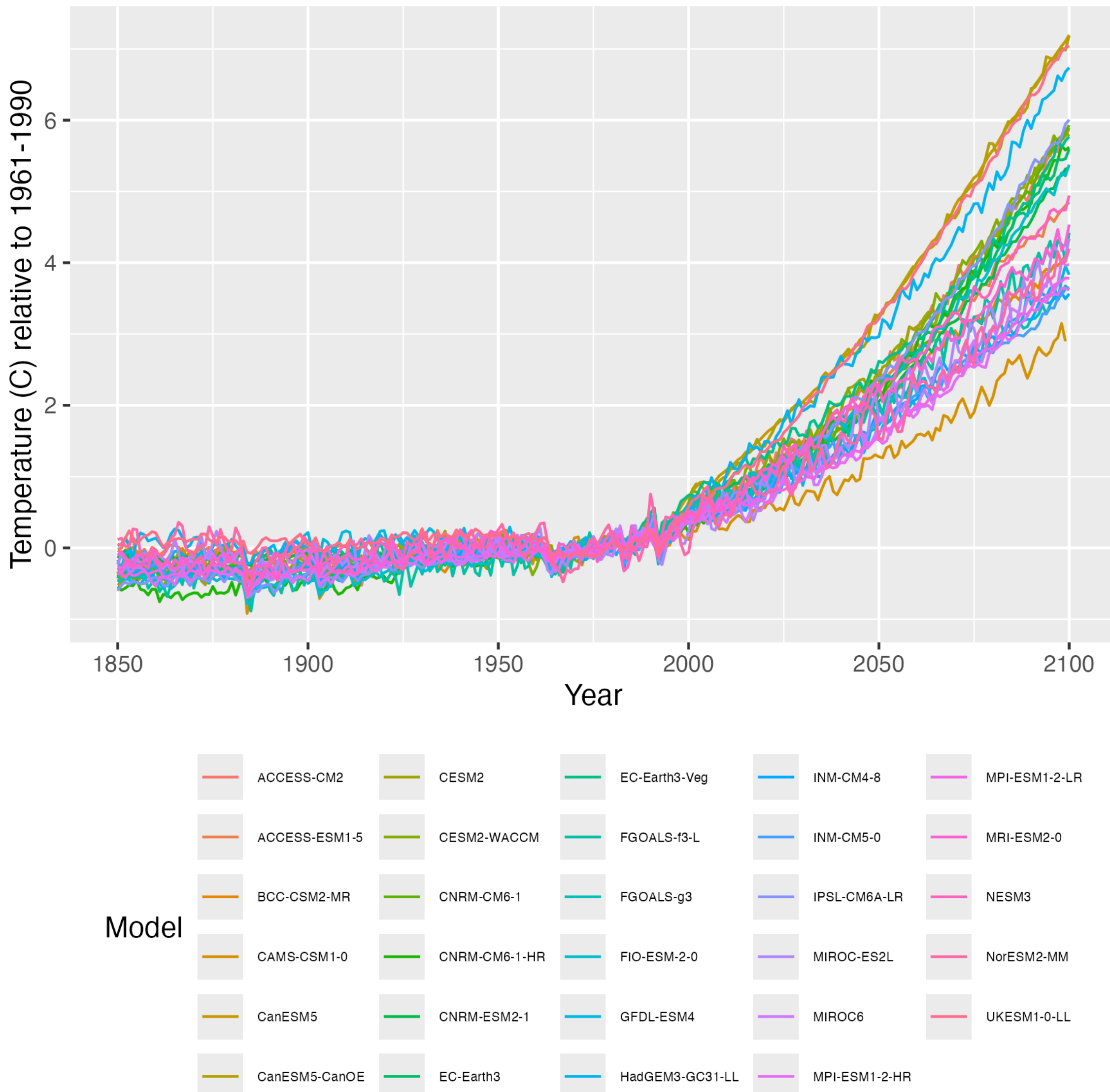
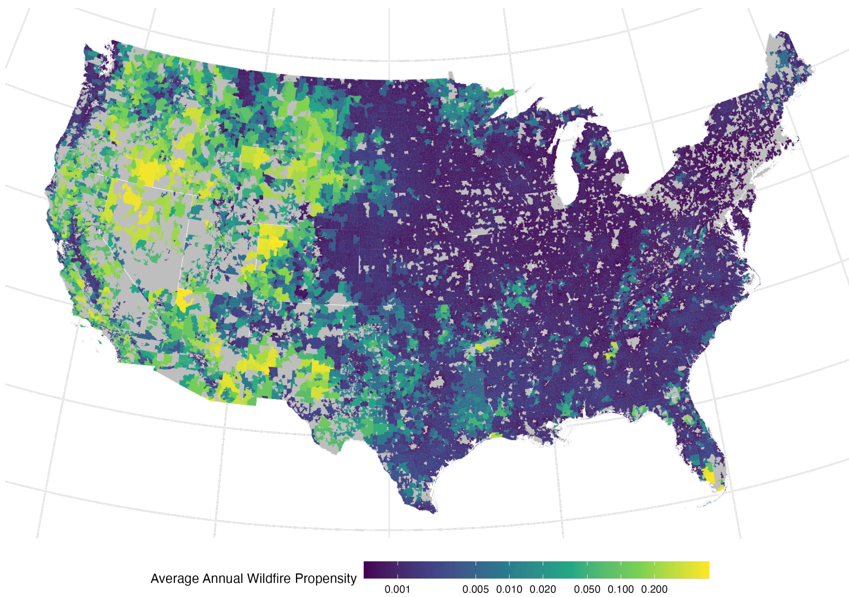


Figure 16: Designing MBS Deals with Evolving Risk – Evolution of the Wildfire Propensity Score

The wildfire propensity score partly determines the composition of a Mortgage-Backed Security whenever the investor chooses a portfolio weight w.r.t. such wildfire propensity score. The upper panel shows the average wildfire propensity score (PS0, first specification) in sample, over the time period of the sample. The lower panel shows the projected change in the wildfire propensity score in 2050. Such change is used to forecast cash flows with increased wildfire risk. The wildfire propensity model is estimated using historical wildfire perimeters. The projected change in 2050 is estimated using the IPCC's CMIP6 projected temperatures and the wildfire propensity model of this paper.

(a) Initial In Sample Wildfire Propensity Score (Wildfire Propensity Model)



(b) Projected Change in the Wildfire Propensity Score (CMIP6 Forecast + Wildfire Propensity Model)

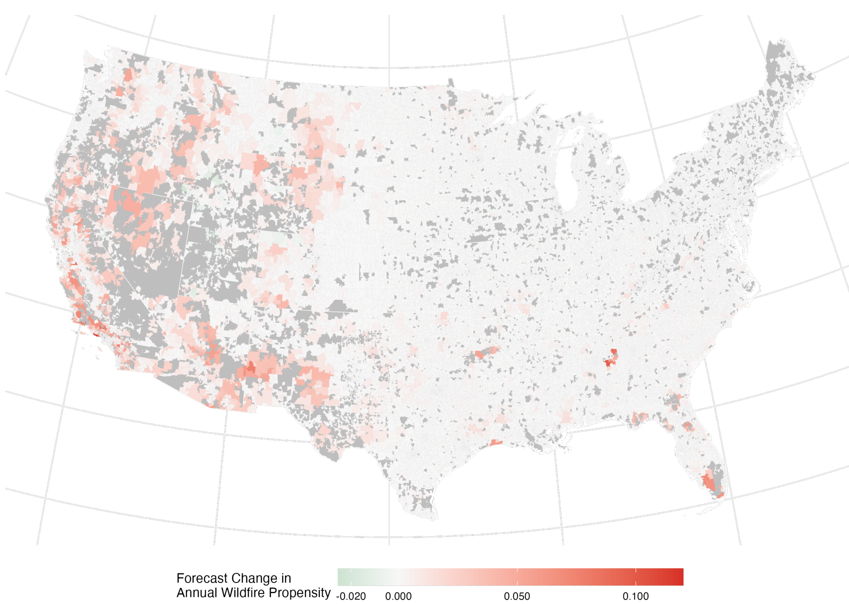
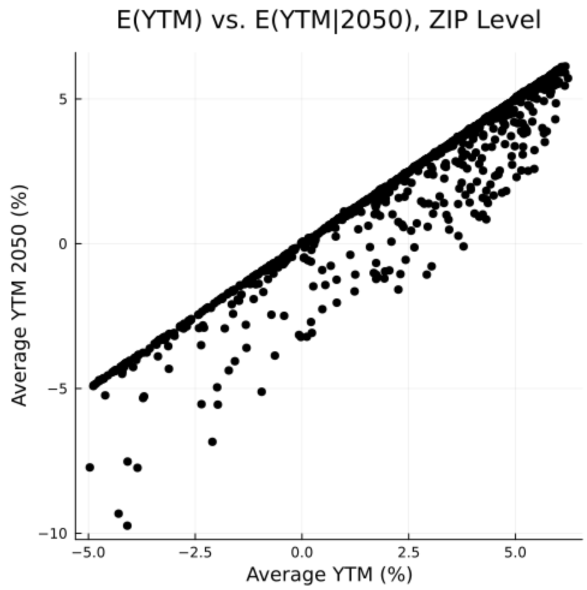


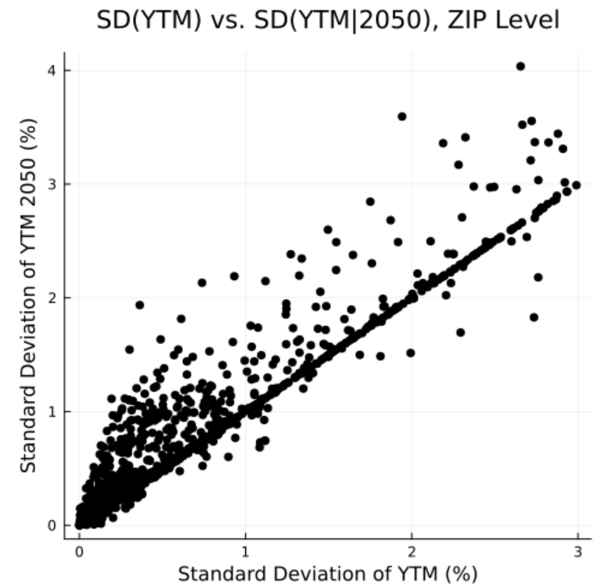
Figure 17: Designing MBSs – Simulated Pools and their Performance, with Rising Temperatures

We simulate cash flows with the wildfire propensity score obtained with projected 2050 temperatures, keeping the correlation in wildfire risk across ZIP codes constant. The upper panels show the change in average returns and the standard deviation of returns. The lower panel shows the change in the allocation of origination dollars, for a 100-million dollar pool.

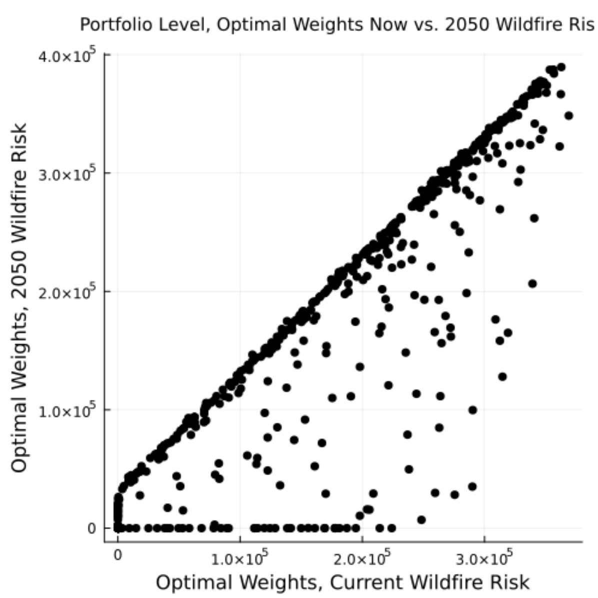
(a) Change in Expected Returns, ZIP-Level, Now to 2050 Risk



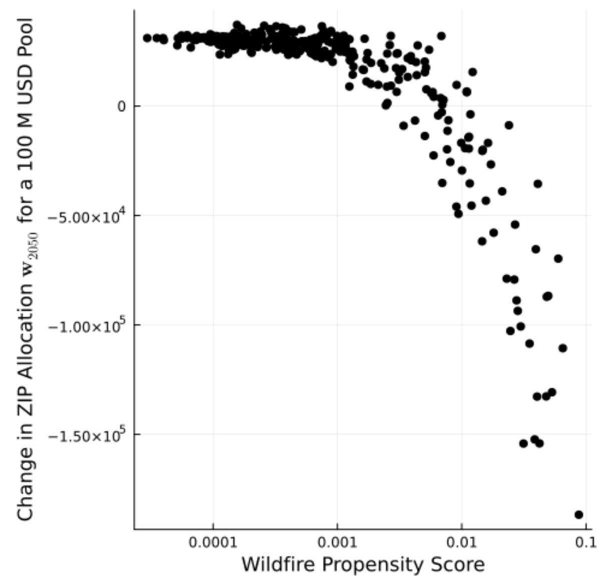
(b) Change in Standard Deviation of Returns, ZIP-Level, Now to 2050 Risk



(c) Optimal Allocation of Dollars, Western States, 100 M USD MBS



(d) Change in Optimal Allocation of Dollars, Western States, by Propensity Score

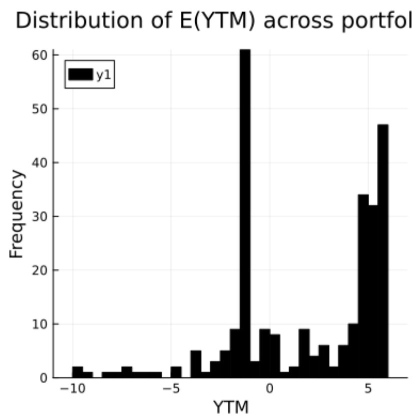


Yield-to-maturity computed according to the formula of equation (20). Panel (a) shows $\mathbb{E}[\mathbf{R}_{j0}]$ for each ZIP code j. Panel (b) shows $SD[\mathbf{R}_{j0}]$ for each ZIP code j.

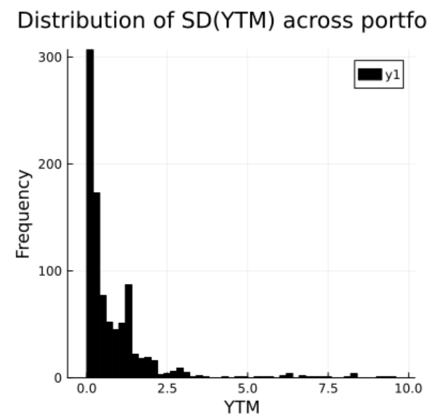
Figure 18: Suboptimal Portfolios: Distribution of Return and Risk, Impact of 2050 Wildfire Risk

These figures present the performance of a range of 1,000 suboptimal portfolios obtained by simulating portfolio weights with normally distribution Koijen & Yogo (2019) portfolio coefficients. These portfolios are suboptimal in the sense that they do not solve the regularized mean-variance problem (14). Panel (a) presents the distribution of portfolio-level expected yield-to-maturity across simulations. Panel (b) presents the distribution of portfolio-level standard deviation of yield-to-maturity.

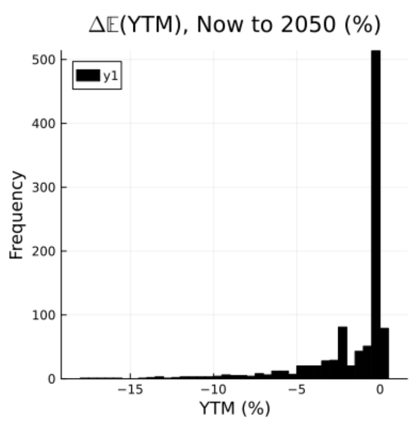
(a) The Long Tail: Simulated Expected Returns



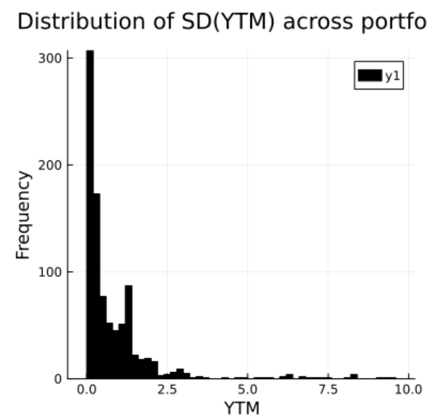
(b) The Long Tail: Simulated S.D. of Returns



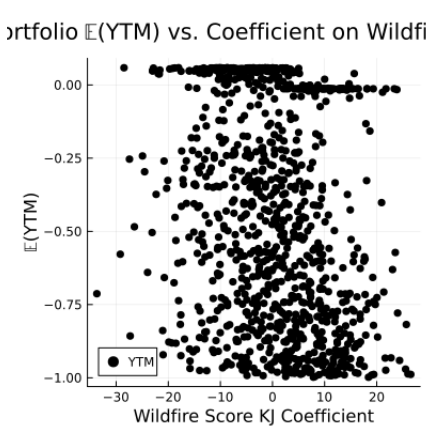
(c) The Long Tail: Changes in Expected Returns, 2050 Wildfire Risk



(d) The Long Tail: Distribution of Changes in S.D. of Returns, 2050 Wildfire Risk



(e) Expected Returns and Wildfire Risk



(f) S.D. of Returns and Wildfire Risk

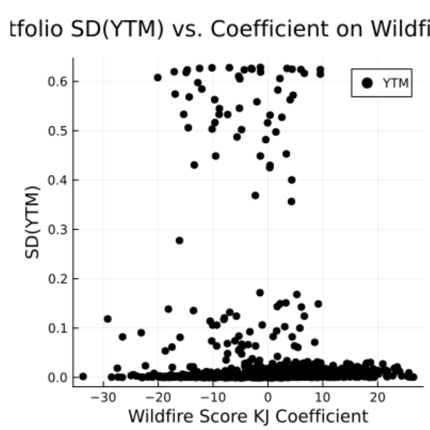


Table 2: Wildfire Propensity Score – Predicting of Wildfire Occurrence at the ZIP Code Level

*This table presents the estimation results from logistic regressions of a wildfire in ZIP code in a month from January 2001 to December 2021. The dependent variable is a dummy variable that takes the value of one if there is a wildfire in a month in a given month and zero otherwise. Abnormal temperature is the monthly temperature net of the mean of temperatures in a calendar month calculated from 1980 to 2000. Mean temperature is the monthly average temperature in a ZIP code from 1980 to 2000 and fixed for a ZIP code. Drought index is the ZIP code-level DSCI and in log terms. Forest share is the share of forest area in a ZIP code area in a given year. Developed area share is the share of developed area in a ZIP code area in a given year. Electricity lines are the length of all above-ground electricity lines in a ZIP code. Similarly, road length is the length of all roads in a ZIP code. We also control for the number of ZIP code-level past wildfires in regression (1). Robust standard errors are clustered at ZIP code level and are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

	Wildfire in a ZIP Code (1=Yes)			
	(1) PS0	(2) PS1	(3) PS2	(4) PS3
Abnormal Temperature	0.211***	0.220***	0.220***	0.219***
	(0.006)	(0.006)	(0.006)	(0.006)
Mean Temperature	0.085***	0.034***	0.035***	0.034***
	(0.002)	(0.006)	(0.006)	(0.006)
ln(Drought Index)	0.060***	0.085***	0.061***	0.061***
	(0.007)	(0.004)	(0.006)	(0.006)
× Forest Share	0.001***		0.001***	0.001***
	(0.000)		(0.000)	(0.000)
Forest Share	0.001*	0.008***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Developed Area Share	-0.007***			-0.008**
	(0.002)			(0.004)
Electricity Lines (m/m2)	53.381			229.448**
	(65.076)			(89.348)
Road Length (m/m2)	-69.315***			-2.862
	(19.036)			(25.910)
ln(ZIP Code Area)	0.212***	0.775***	0.777***	0.740***
	(0.015)	(0.017)	(0.017)	(0.022)
ln(# of ZIP Code-Level Past Wildfires)	1.827***			
	(0.019)			
Constant	-12.622***	-25.116***	-25.059***	-24.275***
	(0.313)	(0.428)	(0.428)	(0.498)
Year FE	–	Yes	Yes	Yes
Month FE	–	Yes	Yes	Yes
State FE	–	Yes	Yes	Yes
# of ZIP Code-Months	6,494,796	6,391,476	6,391,476	6,391,476

Table 3: Mortgage-Level Analysis – Wildfire Exposure and Incremental Foreclosure Probability

*The table presents the two-way DiD regression of the likelihood of foreclosure using equation (2). We obtain propensity scores (PS3) from regression (4) of Table 2. Propensity-score-weighted, robust standard errors are clustered by mortgage and reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

	Foreclosure (1=Yes)			
	(1)	(2)	(3)	(4)
Post-Wildfire (A)	0.505***	0.446***		
	(0.027)	(0.039)		
Post-Wildfire (4 to 12 months) (A)			0.579***	0.579***
			(0.044)	(0.044)
Post-Wildfire (0 to 3 months)			0.311***	0.311***
			(0.042)	(0.042)
Pre-Wildfire (B)		-0.065*	-0.049	
		(0.034)	(0.034)	
Pre-Wildfire(-2 to -4 months) (B)				-0.023
				(0.038)
Pre-Wildfire(-5 to -9 months)				-0.060*
				(0.036)
ln(Loan Balance)	0.424***	0.424***	0.425***	0.425***
	(0.108)	(0.108)	(0.108)	(0.108)
Interest Rate (%)	0.030	0.030	0.030	0.030
	(0.025)	(0.025)	(0.025)	(0.025)
ln(1+Maturity)	-0.055	-0.055	-0.051	-0.051
	(0.116)	(0.116)	(0.116)	(0.116)
Constant	-5.396***	-5.341***	-5.456***	-5.456***
	(0.897)	(0.897)	(0.898)	(0.898)
Mortgage FE	Yes	Yes	Yes	Yes
County×Year-Month FE	Yes	Yes	Yes	Yes
# of Mortgage-Months	29,313,567	29,313,567	29,313,567	29,313,567
Adjusted R^2	0.334	0.334	0.334	0.334
Coefficient Difference (A-B)	–	0.511***	0.628***	0.601***
		(0.027)	(0.032)	(0.037)

Table 4: Mortgage-Level Analysis – Wildfire Exposure and Incremental Prepayment Probability

*The table presents the two-way DiD regression of the likelihood of prepayment using equation (2). We obtain propensity scores (PS3) from regression (4) of Table 2. Propensity-score-weighted, robust standard errors are clustered by mortgage and reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

	Prepayment (1=Yes)			
	(1)	(2)	(3)	(4)
Post-Wildfire (A)	2.483***	1.965***		
	(0.073)	(0.103)		
Post-Wildfire (4 to 12 months) (A)			2.294***	2.291***
			(0.117)	(0.117)
Post-Wildfire (0 to 3 months)			1.654***	1.650***
			(0.114)	(0.114)
Pre-Wildfire (B)		-0.570***	-0.529***	
		(0.088)	(0.088)	
Pre-Wildfire(-2 to -4 months) (B)				-0.106
				(0.089)
Pre-Wildfire(-5 to -9 months)				-0.707***
				(0.093)
ln(Loan Balance)	-10.219***	-10.219***	-10.220***	-10.220***
	(1.273)	(1.273)	(1.273)	(1.273)
Interest Rate (%)	0.418***	0.418***	0.418***	0.418***
	(0.052)	(0.052)	(0.052)	(0.052)
ln(1+Maturity)	8.980***	8.980***	8.997***	8.997***
	(1.405)	(1.405)	(1.405)	(1.405)
Constant	78.317***	78.810***	78.527***	78.530***
	(9.439)	(9.438)	(9.439)	(9.439)
Mortgage FE	Yes	Yes	Yes	Yes
County×Year-Month FE	Yes	Yes	Yes	Yes
# of Mortgage-Months	24,009,159	24,009,159	24,009,159	24,009,159
Adjusted R^2	0.377	0.377	0.377	0.377
Coefficient Difference (A-B)	–	2.535***	2.824***	2.397***
		(0.074)	(0.090)	(0.093)

Table 5: Mortgage-Level Analysis – Loss in a Foreclosure following Wildfires

*This table presents the cross-sectional estimation of loss as a share of unpaid mortgage balance in a foreclosure conditional on that there is a foreclosure in a mortgage. Our control variables include the natural logarithm of the FICO score of the borrower at origination, unpaid balance, an indicator whether the interest rate is adjustable, the natural logarithm of the term to maturity, LTV, and the interest rate of the mortgage. We also add a selection correction following Olsen (1980) in regressions (2) to (6). Robust standard errors are clustered at county level and are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

	Loss-to-Balance Ratio after Foreclosure			
	(1)	(2)	(3)	(4)
Wildfire (1=Yes)	3.932***	4.145***	4.115***	4.462***
	(1.329)	(1.425)	(1.347)	(1.464)
Selection Correction Term		0.013		0.010
		(0.043)		(0.046)
ln(Loan Balance)	-5.268***	-5.624***	-5.501***	-5.919***
	(0.483)	(0.496)	(0.502)	(0.523)
ln(FICO)	2.687*	3.612**	2.079	2.822
	(1.393)	(1.637)	(1.427)	(1.735)
Interest Rate (%)	0.824***	0.647***		
	(0.117)	(0.125)		
ln(LTV)	0.494***	0.510***	0.501***	0.522***
	(0.028)	(0.026)	(0.029)	(0.025)
Adjustable (1=Yes)	1.373	3.180		
	(2.814)	(3.060)		
ln(1+Maturity)	10.238***	10.011***	10.993***	10.912***
	(0.745)	(0.796)	(0.774)	(0.824)
Constant	-13.421	-17.983	-5.776	-9.583
	(10.943)	(12.460)	(10.944)	(13.040)
Deal FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	–	–
Year-Month FE	Yes	Yes	–	–
State×Year-Month FE	–	–	Yes	Yes
# of Loans at Foreclosure	94,772	69,873	93,846	68,949
Adjusted R^2	0.273	0.257	0.283	0.269

Table 6: Deal-Level Analysis – Wildfire Exposure and Cumulative Loss of Deals

*The table presents the two-way DiD regression of the likelihood of cumulative loss of a deal since its inception using equation (12). The wildfire shock is defined as the month in which one or more fires begin and have the greatest impact on the outstanding balance of a mortgage deal. The treatment group includes deals in which the wildfire shock impacts at least 5% of the deal balance in regressions (1) and (2), 10% in regressions (3) and (4), and 15% in regressions (5) and (6). The control group comprises deals either unaffected by wildfires or with less than 5% of the balance impacted. Individual mortgage characteristics are weighted by outstanding balance at the deal level. We obtain mortgage-level propensity scores (PS3) from regression (4) of Table 2. Then, we calculate propensity scores at the deal level weighting them by outstanding balance. Deal-level propensity-score-weighted, robust standard errors are clustered by mortgage and reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

	Cumulative Loss-to-Deal Balance at Origination (%)					
	5% Affected (%)		10% Affected (%)		15% Affected (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Wildfire	2.534		5.983		13.651	
	(1.921)		(4.530)		(8.520)	
Post-Wildfire (3rd year)		9.325		28.036**		45.038***
		(6.383)		(13.968)		(12.761)
Post-Wildfire (2nd year)		5.271		16.554*		25.774***
		(3.740)		(8.751)		(8.949)
Post-Wildfire (1st year)		0.725		1.759		3.455
		(0.580)		(1.422)		(2.890)
Pre-Wildfire	-1.358*	-1.031*	-2.546	-1.436	-6.842*	-4.035
	(0.823)	(0.577)	(1.861)	(1.055)	(4.003)	(2.764)
ln(Deal Balance)	17.497***	17.496***	15.128***	15.126***	12.181***	12.177***
	(1.926)	(1.926)	(2.272)	(2.272)	(2.338)	(2.338)
Weighted ln(FICO)	5.715**	5.715**	5.460**	5.459**	5.065*	5.064*
	(2.247)	(2.248)	(2.596)	(2.596)	(2.730)	(2.730)
Weighted Interest Rate	-9.408***	-9.408***	-9.730***	-9.730***	-8.025***	-8.025***
	(1.096)	(1.096)	(1.557)	(1.557)	(1.861)	(1.861)
Weighted ln(LTV)	0.715***	0.715***	0.728**	0.728**	0.599*	0.599*
	(0.238)	(0.238)	(0.292)	(0.292)	(0.305)	(0.305)
Weighted Adjustable	13.986	13.985	9.435	9.432	8.285	8.278
	(9.152)	(9.152)	(10.828)	(10.828)	(9.983)	(9.982)
Weighted ln(Time to Maturity)	-7.245***	-7.244***	-7.000**	-6.997**	-5.770**	-5.766**
	(2.320)	(2.320)	(2.749)	(2.748)	(2.705)	(2.705)
Constant	-307.082***	-307.077***	-263.350***	-263.312***	-213.691***	-213.622***
	(33.977)	(33.978)	(40.034)	(40.036)	(42.112)	(42.115)
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
# of Deal-Months	111,907	111,907	60,684	60,684	42,738	42,738
Adjusted R^2	0.734	0.734	0.727	0.727	0.722	0.722

Table 7: MBS Deal Analysis – MBS Deal Geographic Diversification and MBS Deals' Unpaid Principal Balance Exposed to Wildfires

*The first column regresses the maximum Unpaid principal balance exposed to a wildfire on the within-MBS deal spatial correlation in wildfire exposure, the log of the Herfindahl index of spatial concentration, the log number of ZIPs in the deal, and the balance at origination. The within-deal correlation is obtained by correlating the ZIP share of dollar housing value exposed to wildfires with the average ZIP share exposed of other ZIPs in the MBS deal in the same year. The Herfindahl is obtained by taking the sum of the squared share of balance in each ZIP, as a fraction of the overall balance in the MBS deal. The deal balance at origination is the highest balance observed for the deal. IID standard errors are clustered at ZIP code level and are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

Dependent Variables:	Max. UPB Exposed to Wildfires $\in [0,1]$	Treated MBS Deal $= 0,1$	log(Herfindahl) $\in (-\infty, 0]$	Within Deal Spatial Correlation $\in [-1,1]$	
Model:	(1)	(2)	(3)	(4)	(5)
Constant	0.1423***	-2.044***	2.633***	-1.227***	-0.7643***
	(0.0517)	(0.4037)	(0.2243)	(0.1212)	(0.0617)
Within-Deal Spatial Correlation	0.0854***	0.4011***			
	(0.0109)	(0.0852)			
log(Herfindahl)	0.0076***	0.0797***			
	(0.0023)	(0.0179)			
log(# ZIPs in Deal)	-0.0228***	-0.1686***	-0.6716***	-0.0508***	
	(0.0048)	(0.0373)	(0.0116)	(0.0115)	
log(Deal Balance) at Origination	0.0041	0.1848***	-0.1226***	0.0704***	0.0350***
	(0.0035)	(0.0276)	(0.0121)	(0.0085)	(0.0029)
Fit statistics					
Observations	1,550	1,550	1,786	1,550	1,550
R^2	0.16081	0.07452	0.78389	0.09742	0.08599
Adjusted R^2	0.15864	0.07213	0.78365	0.09625	0.08540

Appendix Table A: Designing MBSs – Estimation of the Hazard Rate Functions for Portfolio Optimization

This table shows the estimation of the hazard rate function (23) in columns (2) and (4) and the first-stage selection regression (24) in columns (1) and (3). Here Λ is the logit transformation. Regression at the ZIP $\times$ Year-Month level. The heterogeneity of the response of hazard rates to the current 30-year Fixed Rate Mortgage rate is captured by interaction terms of the such rate with the FICO score, the log median household income, and the log median value. Data sources are the Corelogic PLS RMBS mortgage-level data and the American Community Survey.

Dependent Variables:	Any Prepayment	Λ(Prepayment Rate)	Any Foreclosure	Λ(Foreclosure Rate)
Model:	(1)	(2)	(3)	(4)
	Logit	OLS	Logit	OLS
Variables				
Current 30-Year Rate	-8.639***	-33.40***	45.38***	-6.712***
	(2.202)	(1.063)	(2.880)	(1.726)
Current 30-Year Rate $\times$ FICO Score	-0.0993***	-0.0132*	0.0133	-0.0178
	(0.0177)	(0.0072)	(0.0219)	(0.0131)
Current 30-Year Rate $\times$ Log Median Income	-6.260	-8.486***	-1.785	5.598*
	(5.469)	(1.997)	(6.242)	(3.390)
Current 30-Year Rate $\times$ Log Median Value	-9.888**	1.049	9.630**	-0.6035
	(3.907)	(1.508)	(4.117)	(2.484)
Fixed-effects				
5-Digit ZIP Code	Yes	Yes	Yes	Yes
Fit statistics				
Observations	855,185	164,807	565,882	39,123
R^2		0.35123		0.79428

Clustered (5-Digit ZIP Code) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix Table B: Designing MBSs – Sensitivity of Portfolio Optimization to the Regularization Parameter ξ

This table shows the level of portfolio exposure to wildfire risk, for a 100 M USD pool allocated throughout the 5-digit Zip codes of the western states (list in the main body of the paper). The table shows the sensitivity of such portfolio-level wildfire exposure to different values of the regularization parameter ξ when maximizing the mean-variance objective $\mathbf{w}_0'\boldsymbol{\mu} - \frac{1}{2}\rho\mathbf{w}_0'\boldsymbol{\Sigma}\mathbf{w}_0 - \xi\mathbf{w}_0'\mathbf{w}_0$.

Regularization ξ	Min. Wildfire Propensity	Exposure (M USD)
0.0	0.001	60
0.0	0.005	60
0.0	0.01	40
2.5	0.001	39
2.5	0.005	25
2.5	0.01	18
5.0	0.001	40
5.0	0.005	26
5.0	0.01	19
10.0	0.001	40
10.0	0.005	26
10.0	0.01	20

Appendix Table C: Portfolio Coefficients as in Koijen and Yogo, Optimal Portfolio

These tables regress the log portfolio weights of the optimal portfolio for the upper panel (resp. the optimal portfolio with 2050 wildfire risk in the lower panel) on the wildfire propensity score, the log median household income, the log median house value, and the FICO score. These regressions stack the optimal portfolios for Los Angeles, Seattle, San Francisco, San Diego, and for the Western states.

Dependent Variable:	log(Weight, Current Wildfire Risk)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	-10.45***	-2.295	-20.58***	-20.03***	12.03***
	(0.1615)	(4.696)	(3.489)	(0.8050)	(4.616)
Wildfire Score (Annualized)	-0.0163**				-0.0208***
	(0.0071)				(0.0067)
log(Median Income)		-0.7525*			-5.027***
		(0.4261)			(0.5274)
log(Median Value)			0.7849***		1.591***
			(0.2737)		(0.3186)
FICO Score				0.0163***	0.0218***
				(0.0014)	(0.0015)
Fit statistics					
Observations	1,573	1,573	1,573	1,573	1,573
R^2	0.00329	0.00198	0.00521	0.08309	0.13936

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	log(Weight, 2050 Wildfire Risk)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	-10.91***	15.28***	-11.79***	-19.08***	29.64***
	(0.1459)	(4.299)	(3.237)	(0.7809)	(4.147)
Wildfire Score (Annualized)	-0.0485***				-0.0546***
	(0.0067)				(0.0062)
log(Median Income)		-2.406***			-6.358***
		(0.3890)			(0.4783)
log(Median Value)			0.0393		1.336***
			(0.2534)		(0.2896)
FICO Score				0.0134***	0.0218***
				(0.0013)	(0.0014)
Fit statistics					
Observations	1,786	1,786	1,786	1,786	1,786
R^2	0.02894	0.02100	1.35×10^{-5}	0.05432	0.17685

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix Table D: Portfolio Coefficients, Observed Pools

This table present the coefficients of the regression of log(deal weight in ZIP code) on ZIP-level covariates, for each ZIP × pool observation. Deal weight from Corelogic PLS RMBS. Wildfire score calculated by the authors. Median household income and median house value from the 2014 ZIP-level American Community Survey. FICO score from the Corelogic file.

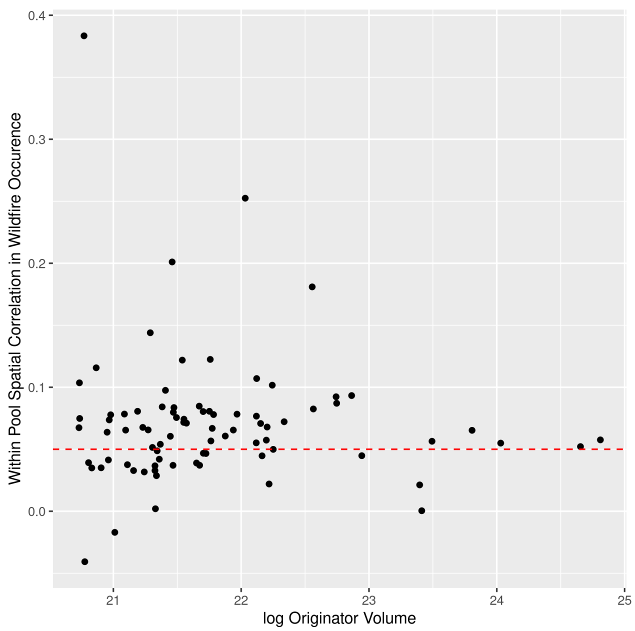
Dependent Variable:	log(ZIP-Level Dollar Allocation)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	-15.26***	-24.79***	-24.45***	-16.07***	-25.79***
	(0.0093)	(0.2001)	(0.1028)	(0.0429)	(0.1423)
Wildfire Score (Annualized)	0.0047***				0.0033***
	(0.0014)				(0.0007)
log(Median Income)		0.8460***			0.1536***
		(0.0179)			(0.0145)
log(Median Value)			0.7164***		0.6350***
			(0.0082)		(0.0094)
FICO Score				0.0015***	0.0012***
				(7.08×10^{-5})	(4.56×10^{-5})
Fit statistics					
Observations	2,687,612	2,687,612	2,625,670	2,687,612	2,625,670
R^2	0.00113	0.13256	0.23466	0.02459	0.25184

Clustered (ZCTA5CE10) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

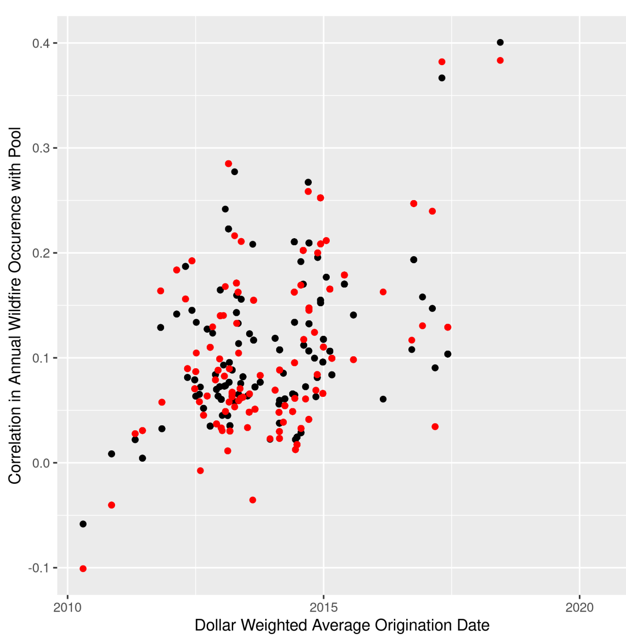
Appendix Figure A: MBS Deal Analysis – Within-MBS Spatial Correlation in Wildfire Risk

For each originator (panel (a)) or for each month (panel (b)), we estimate the within-originator or within-month spatial correlation in wildfire occurrence, weighted by the USD unpaid principal balance in each location. Each point on panel (a) is an originator. Each point on panel (b) is a month. This figure is descriptive as servicers may not report the identity of the originator for all mortgages. Regression analysis later in this paper controls for deal fixed effects and thus uses the longitudinal variation as a source of identification.

(a) By Size



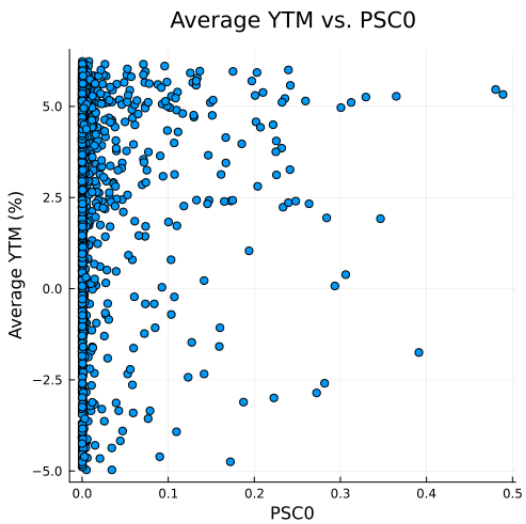
(b) By Origination Date



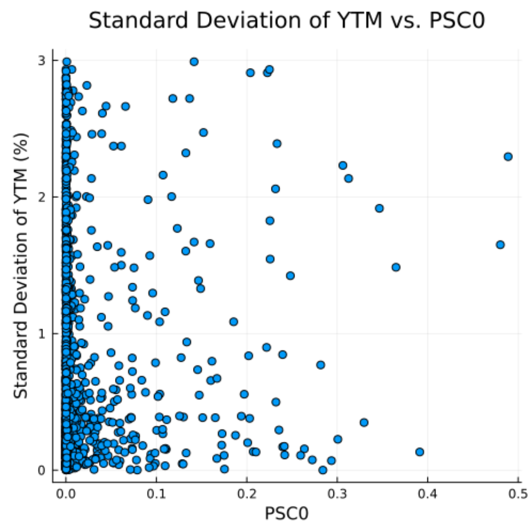
Appendix Figure B: Trade-Offs in Portfolio Optimization – Wildfire Propensity Score, Yield-to-Maturity, Prepayment and Foreclosure Fixed Effects at the ZIP Level

These four panels show that the mean-variance portfolio optimization faces a trade-off when allocating origination dollars to locations exposed to wildfire risk. Panel (a) shows ZIP-level expected returns (yield to maturity) vs wildfire propensity score. Panel (b) shows the standard deviation of ZIP-level returns (ytm) vs wildfire propensity score. Panel (c) shows the prepayment fixed effect of the first stage Heckman ('Any Wildfire') according to specification (23). Panel (d) shows the foreclosure fixed effect of the first stage Heckman ('Any Wildfire') according to specification (23).

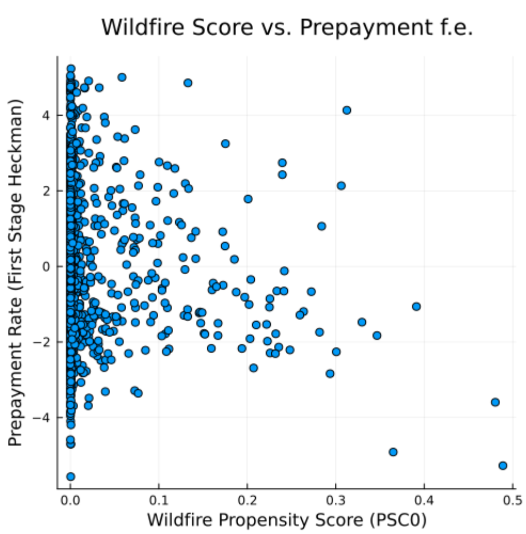
(a) Expected Returns and Wildfire Scores



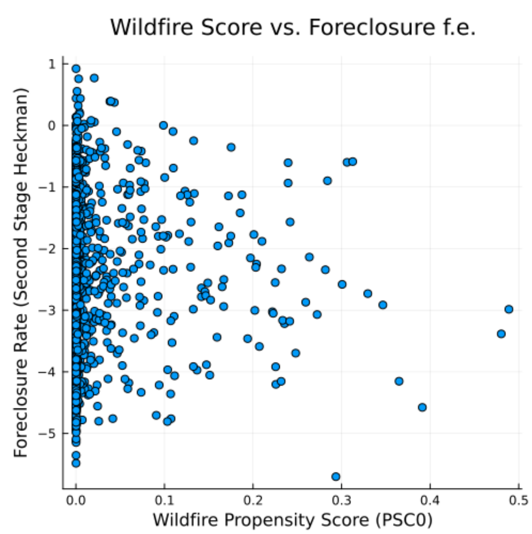
(b) Standard Deviation of Returns and Wildfire Score



(c) Prepayment Fixed Effect, by ZIP, First Stage Heckman



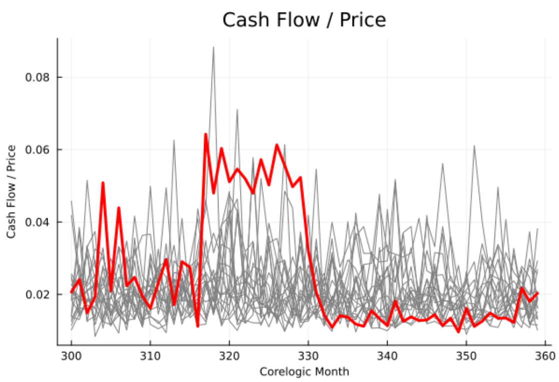
(d) Foreclosure Fixed Effect, by ZIP, First Stage Heckman



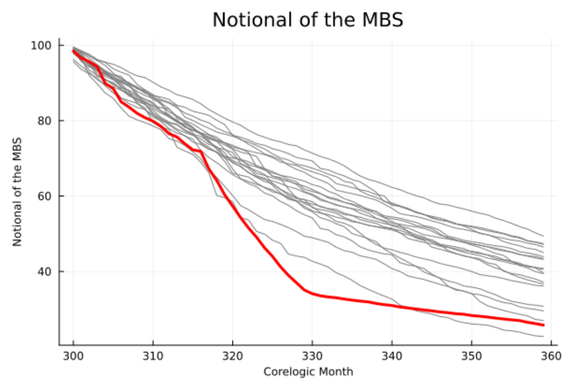
Appendix Figure C: Designing MBSs – Simulation Example, Cash Flow for One 5-Digit ZIP Code, and Monte Carlo Simulations of the 30-year FRM

Panels (a), (b), (c) present the path of cash flows, notional, and price of cash flows for one ZIP code across S Monte Carlo simulations. An MBS is a portfolio of mortgages across such ZIP codes. The red line – is for a simulation affected by a wildfire. Panels (d), (e) are for the zero-coupon bond price (used for discounted cash flows), for the Monte Carlo simulations of the 30-year Fixed Rate Mortgage. Panel (f) is the distribution of mortgage interest rates at origination.

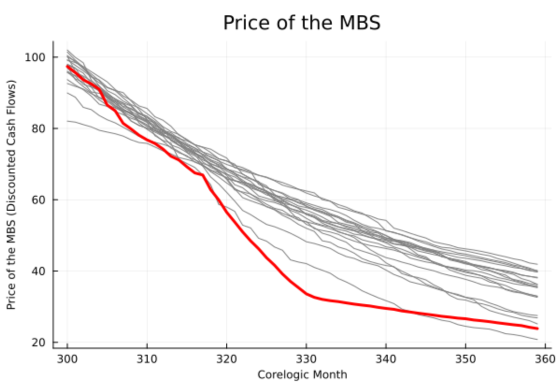
(a) Cash Flow Yield $\mathrm{CF}_{j,t}/p_{j,t}$



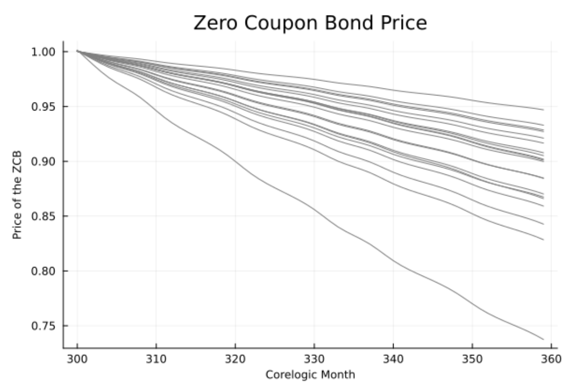
(b) Notional $N_{j,t}$



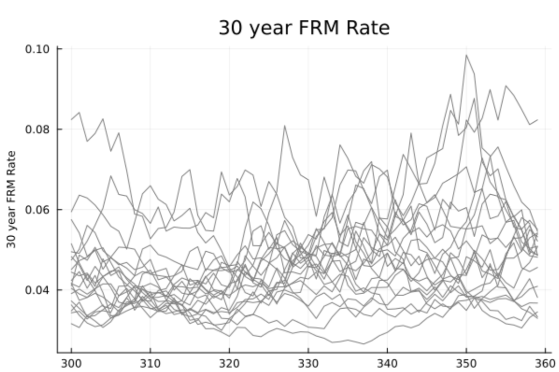
(c) Evolution of the Price $p_{j,t}$



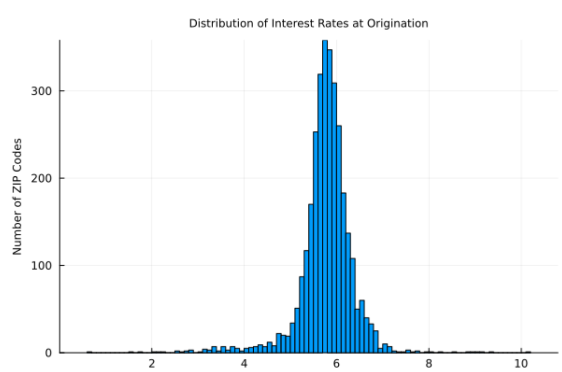
(d) Zero-Coupon Bond Price $\lambda_{j,t}$



(e) Simulations of the 30-Year FRM



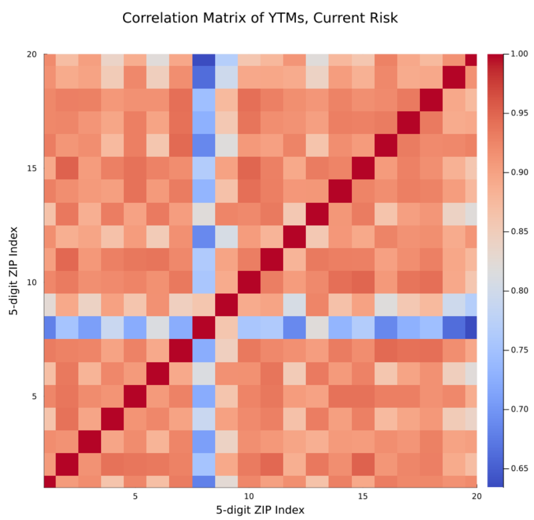
(f) Distribution of Interest Rates at Origination



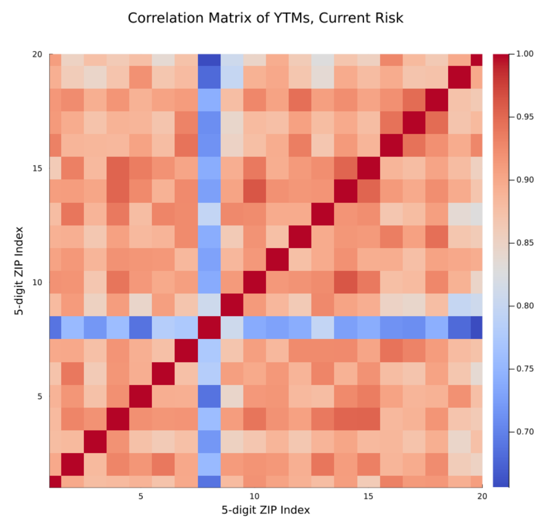
Appendix Figure D: Designing MBSs – Correlation of Monthly Returns Across 5-digit ZIP Codes

This plot displays the correlation matrix for the numerical simulation of yield-to-maturity of ZIP-level mortgage investments $Cor(\tilde{R}_{j0}, \tilde{R}_{j'0})$ *for any pair of ZIP codes* j, j'. *This matrix is denoted* Φ. *An MBS deal can lower the risk (standard deviation of monthly returns) by pooling mortgages from ZIP codes with lower return correlations (lighter shades of gray).*

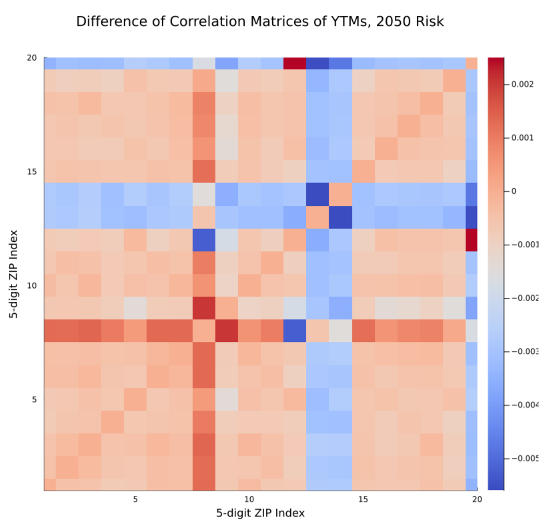
(a) Western States, Correlation Matrix Φ



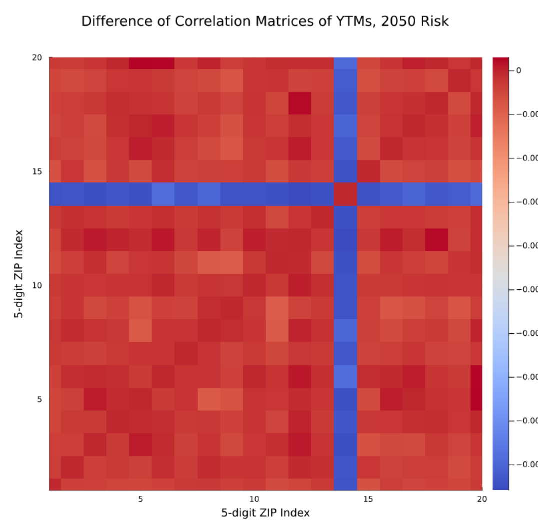
(b) Los Angeles, Correlation Matrix Φ



(c) Western States, Difference $\Theta_{2050} - \Theta$



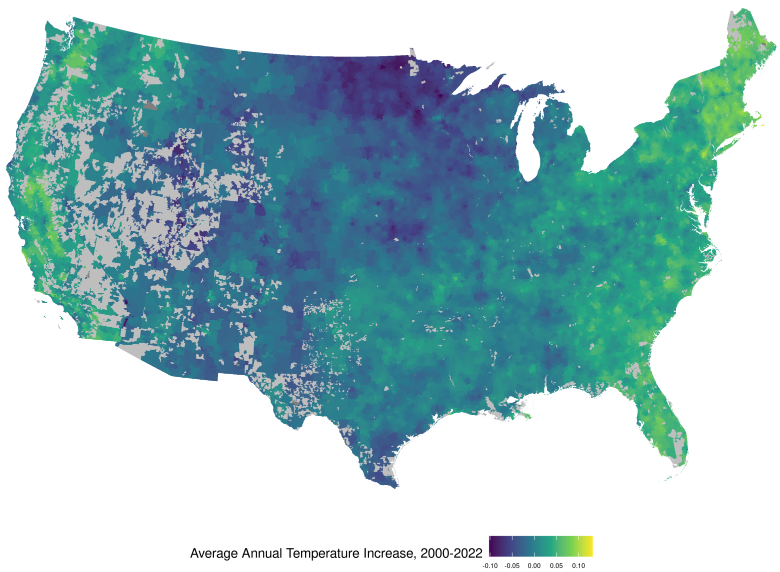
(d) Los Angeles, Difference $\Theta_{2050} - \Theta$



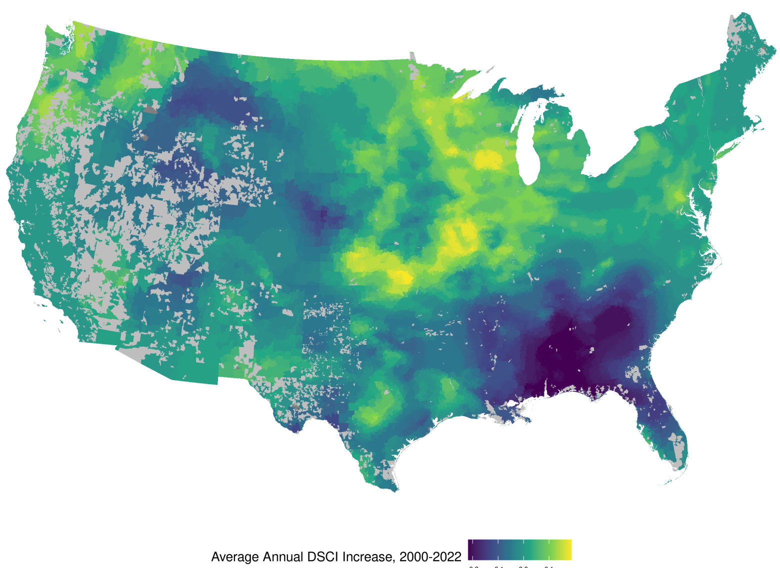
Appendix Figure E: Evolution of Temperatures (PRISM) and of the Drought Index – Average Annual Change

These two maps present the evolution of two key inputs in the Wildfire Propensity Score developed in Section 2.2 and in equation (1). These two key inputs are temperatures and the US Department of Agriculture's drought index, ranging from 0 (no drought) to 4 (exceptional drought).

(a) 5-digit ZIP code Average Annual Change in Temperature (C)



(b) 5-digit ZIP code Average Annual Change in the Drought Index, USDA DSCI (higher is drier).



A Code Appendix

The code for this paper is provided as a single repository and is structured in four parts:

1. The estimation of the ZIP-level and time-varying wildfire score of Section 2, in the `WildfireScore` folder.

2. The estimation of the event study design, of Section 3, in the `EventStudy` folder.

3. The estimation of the optimal pools, of Section 5, in the `Pooling` folder.

4. The estimation of the term structure of risk-free rates, of Section 5.3, in the `HJM` folder.

The optimal pooling code is in the `Pooling/4_optimal_design` folder. Scripts should be run in sequence. The first script `1_get_coupons_and_rate_by_zip.R` relies on Corelogic data stored in a PostgreSQL server. Other scripts rely on publicly available information and the output of the first script is found in the `output/` folder. Construction of the cash flows by ZIP and year-month is performed in R, using the `tidyverse`, `dbplyr`, `RPostgreSQL`, `sf` packages; and portfolio optimization in Julia using the `JuMP` optimizer with the `Ipopt` optimizer. Functions for yield-to-maturity calculations are present in the `ytm_functions.jl` and rely on the root finding algorithm of the `Roots` package.

Cash flow calculations following Chernov et al. (2018) are in the `7_build_ZIP_cash_flow_sample.R` script, around lines 530 to 550.

The optimal portfolio for a specific metropolitan area can be obtained by changing the variable `chosen_MSA` at the beginning of the `10_find_optimal_weights_by_CBSA.jl` script. The portfolio for the Western states (CA, OR, WA, ID, MT, WY, NV, UT, CO, AZ, NM) can be obtained by setting `chosen_MSA` to `US_wide`.

The script `10_map_stats_optimal.R` plots the maps of the initial allocation in dollars by 5-digit ZIP code and of the change in allocation as wildfire risk is increased to 2050 levels.

The script `11_charts_illustrative_mbs.jl` plots the evolution of prepayment rates, foreclosure rates, 30-year FRMs for the S Monte Carlo simulations.

Correlated wildfire draws are generated in the `4_generate_wildfire_draws.R` script.

Hazard rate functions are estimated in the `3_estimate_parameters_hazard.R` script.

B Directory Structure

The following tree diagram shows the complete folder structure and files with extensions: **.r, .jl, .sh, .do, .ado, .tex, .bib, .md**. All other files are counted in the summary above but not displayed in the tree.

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| | |- average_quantile_increases_PRISM.tex (428 B)
| | |- sensitivity_local_DSCI_to_CMIP6_temps.tex (0 B)
| | |- sensitivity_local_temp_to_CMIP6_temps.tex (7.16 KB)
| |- 1_CMIP6_forecasts.r (2.72 KB)
| |- 2_increases_PRISM.r (12.3 KB)
| |- 3_increases_drought.r (7.56 KB)
|- WildfireScore/
| |- data/
| | |- processed/
| | |- raw/
| | | |- drought/
| | | | |- weekly_zip_files/
| | | | |- yearly_zip_files/
| | | |- electric_lines/
| | | |- nlcd/
| | | |- pdsi/
| | | |- prism/
| | | | |- tmax/
| | | | |- tmean/
| | | | |- tmin/
| | | |- roads/
| | | |- shapefiles/
| | | | |- us_cbsa/
| | | | |- us_county/
| | | | |- us_state/
| | | | |- us_zcta/
| | | |- wildfire/
| | |- Foreclosure_Prepayment Definitions.do (542 B)
| |- links/
| |- src/
| | |- drought/
| | | |- 1_process_data.py (2.95 KB)
| | | |- 2_process_output.ipynb (2.68 KB)
| | |- electric_lines/
| | | |- elines.ipynb (4.32 KB)
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| | |- nlcd/
| | | |- 1_process_data.py (1.64 KB)
| | | |- 2_process_output.ipynb (2.91 KB)
| | |- pdsi/
| | | |- pdsi.ipynb (44.25 KB)
| | |- prism/
| | | |- process_data.sh (886 B)
| | | |- process_output.ipynb (2.28 KB)
| | |- roads/
| | | |- road.ipynb (4.88 KB)
| | |- wildfire/
| | | |- 1_merge_fires.ipynb (15.17 KB)
| | | |- 2_find_zip.ipynb (12.71 KB)
| | | |- 2.2_find_zip_neighborhood.ipynb (13.17 KB)
| | | |- 3_unify_fire_effect.ipynb (26.45 KB)
| | | |- 3.2_unify_fire_effect_neighborhood.ipynb (41.15 KB)
| | |- zip_matching/
| | |- 1_zcta_cbsa.ipynb (50.85 KB)
| | |- 1_zcta_county.ipynb (31.08 KB)
| | |- 1_zcta_state.ipynb (33.47 KB)
| | |- 2_zcta_concat.ipynb (5.94 KB)
| |- download_data.sh (6.1 KB)
|- folder_structure.tex (19.59 KB)
|- make_report.r (10.08 KB)
```

- Only files with extensions .r, .jl, .sh, .do, .ado, .tex, .bib, .md are shown in the tree structure.
- All other file types are counted in the summary but not displayed in the tree.
- File sizes are shown in parentheses next to each displayed file.
- File extensions are highlighted in blue.