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 be a drop in the ocean of cash flows. This paper builds a data set of the entire securitization chain from mortgage-level to MBS deal-level cash flows, and observes the prices of the tranches at monthly frequency. 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 an asset demand system that targets return and risk. Extrapolating wildfire risk using a granular wildfire probability model and temperature projections in 2050, we build climate resilient MBSs whose returns are minimally impacted by wildfire risk even as they supply mortgage credit to wildfire prone areas. Finally, we test whether the market prices the sensitivity of each deal's cash flow to wildfire risk.

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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, and extreme rainfall. 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] Authors have assessed whether disaster risk could lead to a new systemic risk factor (Jung, Engle & Berner 2021). Yet, whether these place based risks pose default risks remains an empirical question.

Lenders indeed 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 mortgage.[2] Third, they can charge higher interest rates and structure the mortgage's interest rate 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 (Buchak, Matvos, Piskorski & Seru 2024).

In our recent research (Ouazad & Kahn 2022), we have explored the behavior of major lenders before and after major disasters and have documented evidence that lenders move such loans off of their books.

One potential interpretation of this finding is that this represents adverse selection. Yet, 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 financial institutions' balance sheets is an

[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 the unintended consequences of mandatory flood insurance, see Blickle & Santos (2022).

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 and pricing of risk along the securitization chain. The paper matches pools to their corresponding tranche prices using hand-collected data to estimate whether the risk is priced by financial markets.

First, the paper establishes key facts on the impact of wildfires on mortgage performance, using 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 wildfires on deals depending on their structure.

Third, the paper shows that building an MBS deal with a given exposure to wildfire risk is akin to building a Koijen & Yogo (2019) demand system where the weights are chosen to target moments of the MBS deal cash flows.[3] The paper provides a key result: ways to choose the location of mortgages in a Mortgage-Backed Security to build *climate-resilient* pools. A pool can be diversified in a way that makes its returns resilient to rising global temperatures while providing mortgage credit to wildfire-exposed areas. The Sharpe ratio-maximizing deal features economically significant exposure to wildfire risk. Finally, the paper matches tranche prices to MBS deal cash flows to assess whether physical climate risk exposure is priced, using a 2-step Fama & MacBeth (1973) approach.

[3] The ZIP-level cash flows are built using an approach close to Chernov, Dunn & Longstaff (2018) and Boyarchenko, Fuster & Lucca (2019), adding spatially correlated wildfire shocks that cause prepayments and defaults. Our Sharpe ratios are similar to these papers.

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. The tranches of such pools are also frequently priced by financial markets. This provides with a large *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. This paper builds a local wildfire propensity score that predicts the occurrence of wildfires at monthly frequency with a high fit (type I and type II)[4]. The wildfire propensity score is built using high-quality data collected by multiple federal agencies and our methodology is freely replicable: it uses pre-sample local average temperatures, in-sample local abnormal temperatures, local drought indices of the US Department of Agriculture, land cover data to identify forested and developed areas at the Urban Wildland Interface, electric grid infrastructure, and the road network.

The impact of wildfires on mortgage performance is estimated by carefully 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 × 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. The impact of wildfires on foreclosure and prepayment holds across wildfires in California and the rest of the US and for

[4]Measured using the ROC curve of the ZIP × month logistic regression.

both first wildfires (except on foreclosure) and repeated wildfires. 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. In the aftermath of wildfires, lenders adapt their underwriting standards: new originations tend to have higher interest rates and lower loan-to-value ratios.

We then move from the individual mortgage-level analysis to the MBS deal-level analysis. 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 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. Finally, (3) the time series autocorrelation of wildfire events plays a role when assessing the variance over time spans of multiple months. These three measures also lead to a more negative skewness and a higher kurtosis (thick tails) of the share of an MBS exposed to wildfires.

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.

The impact of wildfires on MBS deals is identified by focusing on events where more than 5% 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 2% or 5% of their unpaid principal balance in locations affected by wildfires tend to experience strictly positive losses in the months following a wildfire.

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 mortgages, similar to a Koijen & Yogo (2019) asset demand system. 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. The coefficients of such asset demand system can be chosen to target specific *moments* of the returns of MBSs: expected return, standard deviation, skewness and kurtosis of returns.[5]

An MBS deal that targets the Sharpe ratio will have a strictly positive volume of originations in areas with high wildfire propensity scores. Such MBS deal will also have negatively skewed cash flows, as wildfires may cause foreclosures and losses.

While the specific choice of the portfolio depends on the preferences of the investor, optimization exercises run in this paper suggest that investors face a trade-off: areas exposed to wildfires tend to have lower baseline prepayment rates and higher interest rates. The Sharpe ratio-maximizing portfolio has a non-trivial exposure to wildfire-prone areas. As temperatures increase, Sharpe ratio-maximizing deals load on wildfire-exposed areas with higher household incomes and higher FICO scores.

The final part of the paper focuses on the market pricing of wildfire risk. The price of MBS tranches reflects investors' expectations about the forward-looking exposure to risk. Such expectations may differ from historical data analyzed so far in the paper, as in Ouazad (2022).[6] This

[5] Of course, if there is a large amount of originations in a location, this will affect the types of mortgages originated, including their rate. The model can be extended to allow for a supply elasticity. This is akin to estimating the demand (by MBS sponsors) and the supply of mortgages (by lenders) as in Berry, Levinsohn & Pakes (1995).

[6] Cf. Mendelsohn, Nordhaus & Shaw (1994), where the hedonic pricing of climate change on farm *values* reflects

paper's main hypothesis – the benefits of pooling for MBS cash flows – does not hinge on the pricing of risk, but rather this section tests whether the market prices the MBS cash flows' wildfire risk exposure. Tranche-level price data at monthly frequency was collected using the Bloomberg Data Service. Each tranche of each deal is sorted by its seniority. We first estimate the sensitivity of each deal's cash flow to (i) the wildfire propensity score, (ii) the term structure of interest rates. An extensive literature has measured the pricing of interest rate risk (Chernov et al. 2018, Boyarchenko et al. 2019, Fabozzi, Bhattacharya & Berliner 2011, Fabozzi 2016), and this paper aims at measuring the possible pricing of wildfire risk *over and above* the pricing of interest rate risk. We show that there is a distribution of betas of cash flows with respect to the wildfire propensity score. While the paper's previous analysis showed the average impact, this part estimates the heterogeneity in deals' responses, as homeowners' insurance coverage and the resilience of housing structures differ across locations.

This is the first step of a Fama & MacBeth (1973) pricing regression. The second step is to perform cross-sectional regressions for each month. We first show that the price (level) of MBS deals exposed to wildfire risk (significant beta) is lower. The discount is larger for more junior tranches, consistent with the structure of tranche cash flows. We then show that the prices adjust more for senior tranches, while price changes are not significant for junior tranches. This suggests that the repricing of risk is more significant for senior tranches, typically ex-ante safer than junior tranches. While the point estimates are suggestive of an impact, the effects are robust in only 15 out of 20 different specifications. While there is a possible signal, it may take more time for the market to price this risk as it increases. These findings are suggestive of an awareness of the risk on cash flows. These suggestive results are consistent with our analysis of the full text of MBS prospectuses dating to as early as 2007 suggesting that investors and sponsors are aware of wildfire risk exposure and climate risk more generally. It also suggests that investors' marginal utility and stochastic discount factors are correlated with wildfire risk. This may be consistent with the literature on MBSs (Gabaix, Krishnamurthy & Vigneron 2007) suggesting that the MBS market is segmented and traded by specialized financial institutions.

a more optimistic belief in forward-looking cash flows than what production functions suggest.

There is considerable literature on the methodological issues surrounding Fama MacBeth estimates. Unlike equity, the tranches of MBS deals present unique econometric questions as they trade over different time periods and amortize. Estimates of the average risk premium correct for Newey & West's (1994) autocorrelation.

This paper contributes to at least four distinct literatures. First, this paper contributes to the literature highlighting the rise of non-bank lenders and the rise of securitization. As the majority of mortgages are originated and distributed, the securitization technology provides a "value-added" that enhances the risk profile of MBSs. Such securitization technology, when guided by the tools described in this paper (spatial correlation, Herfindahl of dollar originations, autocorrelation of risk), provides cash flows with lower variance compared a single undiversified 100 dollars of notional. This paper builds on the insights of Buchak, Matvos, Piskorski & Seru (2023*a*), Buchak, Matvos, Piskorski & Seru (2023*b*), and Buchak et al. (2024). The flat and horizontal view of lenders' balance sheet is indeed incomplete as mortgage lenders are part of a financial network and the cash flows of individual mortgages are increasingly securitized into larger pools.

Second, the takeaways of this paper should be relevant for a broad range of financial participants developing tools to adapt to climate risk. This includes financial participants optimizing the pooling of cash flows of Insurance Linked Securities (ILSs), and of Credit Risk Transfers (CRTs). 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, building on recent seminal papers of asset demand systems. Such asset demand systems could be designed for ILSs.

Third, 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. This is likely to reduce moral hazard, which alleviates concerns about bad informational equilibria that prevent risk pooling. Equity is thus likely a *complement* rather than a *substitute* to pooling for the securitization of cash flows.

Fourth, this paper contributes to the literature on the impact of climate change (Kahn, Mohaddes, Ng, Pesaran, Raissi & Yang 2021), here focusing on security cash flow and pricing. Wildfire-prone areas of our sample experience statistically 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.

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, 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, 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. Natural disaster risk measures such as the wildfire propensity score built in this paper with low false positive rates and false negative rates, can be used to forecast risk with open source and replicable data.

This paper is structured as follows. Section 2.1 presents the private-label RMBS data and the Bloomberg tranche pricing 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 cash flows. The weights of each location in the MBS deal are from an asset demand system. Section 6 then turns to tranche pricing data at monthly frequency, and performs a two-step Fama & MacBeth (1973) approach to measure whether a wildfire risk premium is significant.

2 Data Sources: Cash Flows and Wildfire Risk Propensity

This papers builds a data stack with: (i) individual mortgage cash flows, where the collateral is geolocated, (ii) pool- and deal-level cash flows by aggregating the cash flows of individual mortgages, and (iii) tranche-level prices. To estimate the impact of *climate risk* on (i), (ii), and (iii), we also need data on local natural disaster risk probabilities and occurrence.

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, deal, and then later tranche using the third source of data.

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 prices of MBS tranches were hand-collected using the *Bloomberg Data Service (BDS)* API calls at daily frequency. Corelogic deal identifiers were matched to Bloomberg identifiers using the Bloomberg-Corelogic crosswalk, linking deals to the Bloomberg IDs (BBGID) of the set of traded tranches of the deal. For each BBGID, calls to the BDS API were made to recover the longest possible time series of the last traded price PX_LAST, the bid and the ask, the last update, and the CUSIPs. We check for the liquidity and the quality of the price data by considering 1) the number of deals for which price information is available, 2) the number of months for which the price can be unavailable, i.e. potential gaps in pricing, 3) the number of changes in price from month to month. These statistics are reported in Section 6.3.

2.2 Measuring Physical Disaster Risk at the ZIP Level

We aim to understand how climate risk affects MBS deal cah flows and pricing of these bonds. We particularly focus on wildfires, which are different from hurricanes as hurricanes are more repeated climate events seasonally. On the other hand, wildfire is a one-time event for a specific location or property in our case having a more exogenous nature than hurricanes or flooding. Additionally, wildfires have become a more severe and dispersed climate event with increasing frequency across different geographies. In Figure 1, we show the annual surface area, housing units, and housing value being exposed across the US. In general, we observe an increasing occurrences of wildfires based on all three measures.

[Figure 1 about here.]

Since occurrences of wildfires are increasing, we might also observe wildfires across different locations, more specifically ZIPs in our case, at the same time. Figure 2 presents the spatial correlation across 5-digit ZIP codes in wildfire occurrence using a yearly time window between *t-2* and *t+2*. We see a similar increasing trend in the spacial correlation using surface, housing units, and housing value. Figures 1 and 2 reflect that not only the frequency of occurrences of wildfires is increasing but also the spatial correlation across ZIP codes is going up.

[Figure 2 about here.]

We connect the finance literature to the natural disaster risk literature by building 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 pricing factors that can be included in a Fama MacBeth analysis, and (c) as a way to relate global climate change projections to the ZIP-level probability of wildfires over time.

A Granular Wildfire Propensity Index

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.[7] Our dataset comprises GeoMAC data for wildfires before 2014 and 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.[8]

To predict wildfire propensities, we consider the share of developed and forest areas within a ZIP code, limiting our sample to ZIP codes with at least some 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 shapefiles 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

[7] 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.

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

roads may impede their spread. Electricity lines data are obtained from Homeland Infrastructure Foundation-Level Data.[9]

Temperature data are sourced from PRISM Climate Data.[10] 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, deviated from the mean temperature in a ZIP code. Monthly drought index, another predictor for wildfires, are obtained from ... 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 gets 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 1. 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. 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

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

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

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 1 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 1, 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.

Wildfire propensity regressions are integral to mortgage- and deal-level analyses. In the absence of an adjusted R-squared in logistic regression, we estimate Receiver Operating Characteristic (ROC) curves. These curves illustrate the tradeoff between true positive and false negative outcomes. In Table 1, in-sample ROCs range from approximately 0.97 to 0.98, indicating strong model performance. Out-of-sample ROCs for 2020 and 2021 from the regression that is run until 2019 with the same control variables as in regression (3) without and with fixed effects are more than 0.98 and 0.95, respectively. These strong ROCs affirm the model's robust predictive ability as presented in Figure 3.

[Figure 3 about here.]

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 A 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 A 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.

Indeed, while nationwide data suggest that trends in drought and temperature can be heterogeneous, wildfire-prone states display a rise in drought and extreme temperatures. Appendix Figure B displays the average USDA DSCI drought index and the 90th percentile for California and Nevada. In both cases, the increase in the frequency of wildfires since 2014 coincides with the increase in the drought index and in P90 temperatures. These charts are consistent with the more formal analysis using the propensity score estimated using a logit approach at the beginning of this section.

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

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

where Wildfire_{it} represents a ZIP-code level wildfire covering 10% of the area in a ZIP code, α_i denotes mortgage fixed effects, and $\lambda_{i,t}$ indicates county × year-month fixed effects. Mortgage $\text{Event}_{i,t}$ 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 × 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 1. 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

Main Results

We present our primary findings on mortgage foreclosure and prepayment in Figure 4. In Panel (a), we illustrate the impact of wildfires on mortgage foreclosure using equation (2). Our results indicate that the likelihood of foreclosure starts to increase by the first month following a wildfire, with a persistent increase of approximately 1% within six to 12 months. There is no discernible pre-trend in the nine months before a wildfire, as evidenced by the line intersecting the zero line. Overall, these findings suggest that wildfires significantly elevate the likelihood of foreclosure across the US.

[Figure 4 about here.]

In Panel (b), we shift our focus to the likelihood of prepayment. Our results show that the likelihood of prepayment begins to rise by the second month after a wildfire, experiencing a notable increase of over 4% within 12 months. When examining the pre-trend, we observe a slightly higher likelihood of prepayment (by less than 1%) for treated mortgages before the wildfire, which diminishes until the first month and starts to increase thereafter. The small difference before the wildfire could be attributed to previous wildfires in nearby locations or differential beliefs in climate change by borrowers. We do not expect prior wildfires in other ZIP codes to lead to foreclosure before a wildfire, as foreclosure carries economic consequences for borrowers. However, it is plausible that a borrower may choose to sell their property following a previous wildfire in a nearby ZIP code. Despite this, Panel (b) does not reveal a significant pre-trend issue in our analysis, as post-wildfire months are statistically significantly larger than pre-wildfire months. Overall, our findings suggest that wildfires increase the likelihood of foreclosure and prepayment by 1% and 4%, respectively, within a year following a wildfire.

Cross-Sectional Variation in Mortgage Cash Flows

Before our study, wildfire research predominantly focused on California. Our sample includes both California wildfires and wildfires from the rest of the US. To assess whether our results are influenced by California wildfires or if similar trends are observed in the rest of the US, we interact pre-wildfire and post-wildfire dummies in equation (2) with a California dummy. The results are presented in Figure 5.

[Figure 5 about here.]

Our findings indicate that wildfires in both California and the rest of the US increase the likelihood of foreclosure and prepayment. In Panel (a), we observe a statistically significant 1% increase in the likelihood of foreclosure for California and 1.5% for the rest of the US within 12 months. Confidence intervals are larger for the rest of the US, suggesting greater variation in the impact of wildfires compared to California. Both locations do not exhibit any pre-trend.

Results for the likelihood of prepayment are presented in Panel (b). The likelihood of prepayment increases by around 4% for both California and the rest of the US following a wildfire. While California's results do not indicate a pre-trend, there is a higher likelihood of prepayment in the months before a wildfire in the rest of the US, warranting cautious interpretation. This discrepancy may be due to varying impacts of wildfires on prepayment across different locations, as prepayment can be a choice by borrowers to sell the property.

[Figure 6 about here.]

Figure 6 distinguishes between the impact of the first occurrence of a wildfire in a ZIP code and repeated wildfires in a ZIP code. Overall, the findings suggest that repeated wildfires have a more pronounced impact on the likelihood of both foreclosure and prepayment. In Panel (a), repeated wildfires increase the likelihood of foreclosure by less than 1% within 12 months, with no observable pre-trend. The impact of first wildfires on foreclosure does not reflect an economically significant impact if we compare the months after a wildfire with the months before a wildfire.

In Panel (b), we examine the variation in the impact of the first wildfire and repeated wildfires on prepayment. The likelihood of prepayment increases by 3 to 4% for both the first wildfire and repeated wildfires, with no discernible pre-trend. Notably, there is a larger variation in the impact of first wildfires, as evidenced by the larger confidence intervals. Overall, repeated wildfires have statistically and economically significant impacts on the likelihood of both foreclosure and prepayment while we also observe some impact by the first wildfires in a ZIP code.

Loss in a Foreclosure

After presenting evidence of an increasing likelihood of foreclosure and prepayment, our focus shifts to examining losses following foreclosures. Given that wildfires can directly damage a property and potentially have economic consequences locally, slowing down the neighborhood's economy, we hypothesize that losses in a foreclosure are more substantial.

For this purpose, we conduct a regression of losses conditional on a foreclosure event. Since we can only concentrate on foreclosed mortgages, we control for selection bias, representing the predicted probability of a loan being foreclosed. This is derived from the regression in Panel (a) of Figure 4, following the approach of Olsen (1980). Their method enables us to utilize a broader set of fixed effects by employing a linear probability regression rather than a logistic regression. The results are presented in Table 2.

[Table 2 about here.]

We regress the wildfire indicator along with year-month fixed effects and county fixed effects in column (1). In column (2), we incorporate the selection correction variable (1 - fitted foreclosure probability) as suggested by Olsen (1980), and in column (3), we add mortgage characteristics. The loss-to-balance ratio significantly increases by 4.5% to 6.3% in the presence of a wildfire. In other words, the unconditional recovery rate is 63% after a foreclosure. Wildfires can reduce the recovery rate to less than 57%, based on our findings.

In columns (4) to (6), we include the natural logarithm of FICO scores and its interaction with the wildfire dummy. Our findings indicate that higher FICO scores mitigate the impact of wildfires on foreclosure loss. In simpler terms, borrowers with lower FICO scores experience larger losses following a wildfire. This finding remains robust when using ZIP code fixed effects, as presented in Column 6 of Table 2.

Mortgage Contracts in the Aftermath of Wildfires

Our findings illustrate that wildfires increase the likelihood of foreclosure and prepayment, leading to larger losses in a foreclosure. We also evaluate how lenders respond to loan originations after wildfires, given the heightened risks. This response represents the financial market's initial defense against wildfire risk. We specifically investigate the interest rate and Loan-to-Value (LTV) at loan originations within a year following a wildfire, presenting our results in Table 3.

In columns (1) to (3), we regress the interest rate at origination on a binary indicator for any wildfire in the ZIP code of the collateral property within the last year. We include loan characteristics, year-month fixed effects, and county or ZIP code fixed effects. Columns 2 and 3 focus on loans with an LTV less than 80%, distinguishing our analysis from borrowers potentially healthier and granted LTVs exceeding 80%. Consistently, we find that a wildfire in the previous year increases the interest rate of loans originated by 5.4 to 5.6 basis points, irrespective of location fixed effects or the inclusion of LTV as a control or exclusion of borrowers receiving loans larger than 80% from the sample.

[Table 3 about here.]

In columns (4) to (6), we regress LTV with similar controls and sample restrictions. Our findings indicate that borrowers from ZIP codes affected by wildfires have LTVs 3.1% to 3.5% lower than their peers at origination, controlling for loan characteristics and time and county fixed effects. If we control for ZIP code fixed effects, the decline in LTV for borrowers from affected ZIP codes becomes less than 6%. This effect of wildfires in the previous year reflects variation within ZIP codes. Overall, our findings demonstrate that lenders respond to wildfire risk following wildfires by increasing interest rates and lowering LTVs at loan origination.

4 MBS Deals' Exposure to Wildfires: Diversification, Spatial Correlation, and Impact on Cash Flows

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, then provide evidence that is related to the within-MBS deal spatial correlation in wildfire risk exposure. We then turn to the estimation of the causal impact of wildfire exposure on deal-level cash flows, and explore the sources of heterogeneity explaining the differences in treatment effects across MBS deals.

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

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 Section 3, as locations where more than 10% of the surface area is affected. The share of an MBS affected by such wildfire exposure in month t is then estimated as using such treated ZIP codes:

$$\text{MBS Share Affected}_{jt} = \frac{\sum_{l=1}^{L} \text{Balance}_{jlt}\text{TreatedZIP}_{lt}}{\sum_{l=1}^{L} \text{Balance}_{jlt}} \tag{3}$$

where l indexes 5-digit ZIP codes, j is the deal, and Balance_{jlt} is the unpaid principal balance in location l for MBS j at the beginning of time t. For MBSs, we use deals.

The Variance of MBS Exposure: Correlation and Concentration

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 is formally visible when considering ex-ante the distribution of the random variable $\widetilde{\text{Wildfire}}_{jt}$ for deal j in month t, the aggregation of wildfire shocks for each mortgage.

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

where $\ell(i)$ is the location of mortgage i, and $\widetilde{\text{Wildfire}}_{\ell(i)t} = 1$ whenever a wildfire hits location j, and zero otherwise.[11]

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

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

[11] 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.

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

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

the correlation that any pair l, l' of locations experiences a wildfire in the same time period.[12] The variance of deal-level wildfire exposure depends on the (i) correlation between locations and on the (ii) concentration of risk:

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

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:

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

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.

Specifying the way the deal-level correlation is estimated allows us to estimate standard errors for this parameter as well. This distinguishes the random occurrence of joint events from the occurrence of genuinely correlated shocks.

[12] The correlation can be made to depend on any pair of locations.

The correlation can be simply estimated as the regression coefficient of wildfire occurrence on average wildfire occurence for other ZIPs of the MBS:

$$W_{j\ell t} = \mathrm{C}_j^{\mathrm{st}} + (\rho_j \mathrm{Var}_j)\, \overline{W_{j-\ell t}} + \varepsilon_{j\ell t} \tag{9}$$

where $\overline{W_{d-\ell t}}$ is the average frequency of wildfires in other locations of the MBS deal d at time t. The regression is weighted by deal's dollar balances $b_{j\ell t}$ in each location. The correlation $\widehat{\rho}_j = \widehat{Cov}_j / \widehat{\mathrm{Var}}_j$ is the ratio of the estimated coefficient and the estimated variance. The distribution of the estimate of the covariance $\widehat{Cov}_j$ is obtained by simulating wildfire occurrences W_{lt} across locations using the estimated variance-covariance for the locations of the deal. The variance of the sample of covariance estimates is the variance of the estimator of the covariance on the sample. This process is repeated for each deal, knowing its vector b_{jlt} of shares of unpaid principal balance.

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 formed at origination in a way that is both correlated with wildfire propensity and with 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, for each first wildfire event of an MBS deal, treated MBS deals are compared 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 7(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 8 presents the same statistics by month for three different thresholds.

$$\text{Treated}_{dt} = \mathbf{1}\left(\frac{\sum_{j=1}^{J} \text{Balance}_{djt}\text{Treated ZIP}_{jt}}{\sum_{j=1} \text{Balance}_{djt}} > \text{Threshold}\right) \tag{10}$$

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 7 about here.]

[Figure 8 about here.]

Treated Deals and Spatial Concentration

Table 4 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.

$$\begin{aligned}\text{Treated}_{dt} &= \text{Constant} + b_1\text{Spatial Correlation}_d + b_2 \log(\text{Herfindahl}) \\ &\quad + b_3 \log(\#\text{ ZIPs in Deal}) + b_4 \log(\text{Deal Balance at Origination}) + \text{Residual}_{dt} \quad (11)\end{aligned}$$

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 4 about here.]

Our findings in Table 4 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 9, 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 sparial 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 9 about here.]

Econometric Specification

The specification uses the event study data to estimate the impact of wildfires on deal-level loss amounts normalized by the total dollar value of a deal.

$$\begin{aligned}\text{Deal Loss}_{i,t} = \alpha_i + \lambda_{i,t} + \beta_1 \text{First Wildfire Exposure}_{it} \times \text{PRE}_t \\ + \beta_2 \text{First Wildfire Exposure}_{it} \times \text{POST}_t + \epsilon_{i,t}\end{aligned} \tag{12}$$

where First Wildfire $\text{Exposure}_{d\iota} = 1$ when deal d has been exposed to a wildfire event. Deal Loss_{dt} is a measure of the share of losses as a fraction of the deal's unpaid principal balance. A wildfire event is considered when at least one deal has had more than 2% or 5% of its UPB 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 by less than 1%. 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, interest rates, loan-to-value ratios, and amortization structure of the mortgages. Standard errors are double-clustered at the deal and the year-month levels.

4.3 Results

Results are presented on Figure 10. In Panel (a), we present the results of analysis using treated deals that are affected by more than 2% of a deal. The sample exludes deals that are affected by between 1% and 2%. In Panel (b), we use deals that are affected by more than 5% of the deal balance and similarly exludes deals that are affected by between 1% and 5%. The event time used ranges from month t-9 to t+36.

[Figure 10 about here.]

Both panels reflect that the early months following the wildfire do not constitute any impact on deal losses. However, the losses start to increase thereafter. Compared to mortgage-level results, this is expected as the losses appear after some attempts for resolution. For the treated deals with more than 2% affected, the loss as a share of unpaid principal reaches to 0.5 ppts. For treated deals with more than 5% affected, the loss increases to more than 0.5% of the deal. The impact is statistically significant and persistent up to 36 months. We only see some decline in the impact after the 28th month for the treated deals affected by more than 5%. We also do not observe any significant pre-trend back to nine months before the wildfire starts. Overall, our findings demonstrate that the increased probability of foreclosure following wildfires is carried over the deals similarly with larger losses following a wilfire affecting a deal.

5 Designing MBS Deals by Building 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 the US's more than 32,000 ZIP Code Tabulation Areas.

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, 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 dynamic of interest rates, using a Heath, Jarrow & Morton (1990) approach that forecasts the entire yield curve using four factors.

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 *at given pooling*. Yet, when MBS pools are re-optimized, the impact on returns and risks is significantly smaller.

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 monthly return $\tilde{r}_t$. 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 50 simulations of interest rates and wildfires. 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, the skewness, and the kurtosis of returns. Fixed income investments have, by nature, skewed and leptokurtic returns. When focusing on the mean return and the standard deviation of returns, we can use the Sharpe ratio, as in Boyarchenko et al. (2019) and our numerical estimates of the Sharpe ratio are consistent with this paper.

The dimensionality problem can be an issue when dealing with optimal allocations of dollars of mortgage originations across a large number of ZIP codes of the coterminous US. We can reduce such dimension by using selecting portfolio weights in a Koijen & Yogo (2019) demand system. The optimization here targets moments of cash flows, as a Lucas Jr (1978) tree investor who consumes the cash flows of the MBS deal in every period. Formally, the goal is to choose the coefficients of the demand system that maximizes the present discounted utility of cash flows over the life of the MBS deal. We denote these coefficients by ω^w for the portfolio coefficient for wildfire risk, and by $\boldsymbol{\omega}$ for the other ZIP-specific covariates. They pin down the dollar allocation in each location j, a positive[13] vector $(w_{j,0}) = \boldsymbol{w}_0$ that sums to 1.

The monthly stochastic return of the pool is due to (i) the decline of the notional, due to prepayments and foreclosures and (ii) the cash flow of the pool, due to coupon payments, prepayments and foreclosure sales:[14]

$$\tilde{r}_t(\boldsymbol{w}_0) = \frac{\widetilde{N}_t - \widetilde{N}_{t-1}}{\widetilde{N}_{t-1}} + \frac{\widetilde{\mathrm{CF}}_t}{\widetilde{N}_{t-1}} \tag{13}$$

The cash flow of the deal CF_t is the aggregation of the cash flows of individual mortgages.

$$\widetilde{\mathrm{CF}}_t = \sum_{j=1}^{J} w_{j,0} \underbrace{(\widetilde{N}_{j,t} c_j + \widetilde{\lambda}_{j,t} \alpha_{j,t} I_{j,t})}_{\text{Cash Flow } \widetilde{\mathrm{CF}}_{j,t} \text{ at Location } j} \tag{14}$$

$\widetilde{N}_{j,t}$ is the dollar notional at location j in month t. c_j is the coupon rate in location j. When

[13] We do not allow the short-selling of mortgages in this exercise.

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

mortgages are fixed rate mortgages (FRMs), this is $c_j = r_j(1+r_j)^T/((1+r_j)^T - 1)$. 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 $\widetilde{N}_{j,t}$ declines at speed the hazard rate $\widetilde{\lambda}_{j,t}$, as:

$$\widetilde{N}_{j,t+1} = (1 - \widetilde{\lambda}_{j,t})\widetilde{N}_{j,t} \tag{15}$$

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 increases when a wildfire occurs, consistent with the results of Section 3.2. When mortgages prepay only, $\alpha_{j,t} = 1$. For private-label MBS deals, the investor may lose part of the balance, and $\alpha_{j,t} \leq 1$.

The hazard rate of prepayment and foreclosure $\widetilde{\lambda}_{j,t}$ depends on (i) borrowers' incentives to prepay, based on the difference between the current mortgage rate r_t^{30y} and the national mortgage rate at origination at the location r_0^{30y}; and it depends on (ii) the occurrence of wildfires at location j.[15]

$$\log\left(\frac{\widetilde{\lambda}_{jt}}{1-\widetilde{\lambda}_{jt}}\right) = \log\left(\frac{\lambda_j^0}{1-\lambda_j^0}\right) + \zeta(r_0^{30y} - \tilde{r}_t^{30y}) + \delta\widetilde{\text{Wildfire}}_{jt} + e_{jt} \tag{16}$$

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.

Each location has a specific base hazard rate λ_j^0. 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 et al. 2011, Fabozzi 2016, Chernov et al. 2018, Boyarchenko et al. 2019).

Denoting by $w_{j,0}$ the weight of location j in the deal at origination $t = 0$, the log weight is expressed as a function of the wildfire propensity score and a vector of covariates for the location:

$$\frac{w_{j,0}}{w_{0,0}} = \exp\left(\omega^w \text{Wildfire PS}_j + \mathbf{x}_j\boldsymbol{\omega}\right)\varepsilon_{j,0} \tag{17}$$

[15] The mortgage rate at origination is absorbed by the fixed effect.

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, but may also include the characteristics of the mortgages such as LTV, interest rate, and amortization structure.

The difference here with a McFadden (1974) approach is that the coefficients ω^w and $\boldsymbol{\omega}$ are *chosen* to maximize the intertemporal utility of the investor. A more complex problem would be to select the dollar investment in each location separately, but the more than 30,000 5-digit ZIP codes make this approach infeasible. Rather the parameterized approach of equation 17 is a low-dimensionality approach to allows us to focus on a small set of coefficients. In this approach we pick the dollar origination volume in each location at $t = 0$ and the mortgages amortize over $t = 1, 2, ..., T$.

Simulating future hazard rates for a given pool composition takes two inputs: a model of the term structure of interest rates, and a model of wildfire occurrence. We start with wildfire occurrence.

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.[16]

$$P(\text{Wildfire}_{jt}) = \text{PS}_{jt}, \quad \text{Cor}(\text{Wildfire}_{jt}, \text{Wildfire}_{j't}) = \rho_{s(j)}, \quad \text{if } s(j) = s(j') \tag{18}$$

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.

The investor takes as given: the ex-ante probability of wildfires PS_{jt} across the 360 months of the mortgage, the ex-ante spatial correlation ρ_s within each state s, the coupon rate c_j in each

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

location, the baseline hazard rate λ_j^0 and recovery rate α_j in each location, the ex-ante probability distribution $f(\tilde{r}_t^{30y})$ of interest rates in future periods.[17]

For the forecast of the 30-year mortgage rate, we model the stochastic process of interest rates using the workhorse Heath et al. (1990) approach to the modeling of the term structure. The 7-year Treasury plus a stochastic FRM premium is used to predict the 30-year mortgage rate. We estimate the 7-year by taking the product of the forward rates estimated by the factor decomposition of Heath et al. (1990).

The starting point of the optimization problem matters as the information set Ω of the investor is different in each month t. First, 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.[18] Third, when such forward-looking term structure is plugged-in to the hazard rate equation, this provides the forward-looking probabilities of prepayment and foreclosure.

Trade-Offs Between Wildfire Exposure and Prepayment, Foreclosure Risk

The portfolio optimization problem will have a non-trivial solution as there is a *trade-off*: households in wildfire exposed areas tend to have lower baseline prepayment and foreclosure risks.

We describe this trade-off in Appendix Table A. This table presents cross-sectional regressions of the baseline hazard rate of prepayment (column (1)), the baseline hazard rate of foreclosure (column (2)), and the interest rate (column (3)) on the average value of the wildfire propensity score. These regressions suggest that ZIP codes with higher wildfire propensities tend to have lower *baseline* odds of prepayment (upper panel). The third column of the lower panel suggests that areas with higher wildfire risk tend to have higher interest rates. This suggests that, at the minimum, there are non-trivial trade-offs. Investors may thus want to hold non-zero exposure $\omega^w > 0$ to areas

[17] Investors may not take the characteristics of mortgages as exogenous, e.g. the coupon or the LTV. Extensions of this approach may include understanding how MBS sponsors vertically integrated with originators change the Loan-to-Value requirements or the amortization structures offered to borrowers. Originators can provide incentives to fortify homes. Another possible extension of the model is to allow for an interest rate response when credit supply increases. Literature suggests that credit supply affects location choices (Ouazad & Rancière 2019).

[18] 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.

with higher wildfire propensity scores.

5.1 Empirical Results: Exposure to Wildfires and the Moments of MBS Cash Flows

We simulate 1,000 MBSs across 50 simulations of interest rate paths and wildfires. We focus on the following states for computational reasons: California, Oregon, Washington, Indiana, Montana, Wyoming, Nevada, Utah, Colorado, Arizona, and New Mexico. Creating an MBS with lower wildfire propensity scores, with mortgages in New York and New England would lower the risk of the pool but may have non-trivial impacts on expected returns.

We start by describing the benefits of pooling risk across ZIP codes by bundling mortgages across mortgages. Table 5 displays the distribution of the returns for our simulated MBS deals across different portfolio weights $(\omega^w, \boldsymbol{\omega})$ (rows 2,4,6), alongside the distribution of ZIP-level returns (rows 1,3,5). The first two rows compare the average monthly returns on investing the entire origination amount in one ZIP code vs any of the simulated MBSs. The next two rows describe the standard of returns, and the last two rows the Sharpe ratios. The main benefit of pooling that this table suggest is that it smoothes the tail risk of individual ZIP codes, reducing the standard deviation by 58.7% = (3.18-7.71)/7.71 for the median ZIP code compared to the median MBS deal. This leads to a distribution of returns with thinner tails and in particular the lower tail of monthly returns.

[Table 5 about here.]

This benefit of pooling mortgages across locations arises as the returns are imperfectly correlated. Appendix Figure D plots the correlation matrix for the ZIP codes of our sample. Each row and each column is a ZIP code, and the shades of gray correspond to the correlations $\text{cor}(\tilde{r}_{jt}, \tilde{r}_{j't})$ for any pair j, j' of ZIP codes. It shows that, while some pairs have correlated returns due to prepayment probabilities driven by macroeconomic shocks (Chernov et al. 2018), other pairs have lower correlations (lighter gray colors) and the standard deviation of returns can be lowered by pooling them in the same MBS deal. This correlation matrix is, up to constants, the covariance matrix Σ of a standard Markowitz (1991) portfolio optimization exercise.

In Table 5, the Sharpe ratio is calculated using a risk-free rate of 1.7% corresponding to the yield of the 5-year Treasury (FRED series DGS5) on January 2nd 2014, which is the starting point of our simulations. The median simulated pool has a return of 5.03%, a standard deviation of 3.18ppt, and a Sharpe ratio of 1.04, which is consistent with prior literature. The expectation and the standard deviation of returns are estimated across months and across simulations:

$$\widehat{E}(\tilde{r}_t) = \frac{1}{ST}\sum_{s=1}^{S}\sum_{t=1}^{T} r_{s,t} \tag{19}$$

with $S = 50$ and $T = 360$.

Figure 11 presents the baseline distributions of expected returns, standard deviation of expected returns, and sharp ratios of the simulated pools. Panel (d) also presents the dollar allocation of loan originations by wildfire propensity score in the sumulated MBS. The upper panels of Figure 11 suggest a thick tail of MBS returns (a),standard deviations (b), and sharp ratios (c) with most deals' performance around the average and some deals with significantly lower returns, higher standard deviations, and lower sharp ratios. This is consistent with the paper's finding when analyzing actual deals of the PLS RMBS market (Table 4): undiversified deals may significantly underperform better designed deals.

[Figure 11 about here.]

Panel (d) of Figure 11 displays the dollars invested in each location when starting with a 100 million dollar balance and investing it across locations to maximize the Sharpe ratio. This figure suggests that the Sharpe-ratio maximizing pool has non-zero exposure to wildfire risk. Similarly, the results of our portfolio optimization exercise by selected locations are displayed on the upper panels of Figure 12. While the optimal, Sharpe Ratio-maximizing pool, includes mortgages from across the states of our analysis, we focus here on the dollars originated in San Francisco and Los Angeles for clarity. The maps suggest indeed that the Sharpe ratio maximizing pool invests dollars in Northern and North-East Los Angeles, as well as the Northern Bay area, which have higher wildfire propensity scores. These findings are consistent with panel (d) of Figure 11.

[Figure 12 about here.]

While the two maps of the upper panel of Figure 12 presented the Sharpe ratio maximizing pools, the two maps of the lower panel of Figure 12 present the geographic allocation of dollars for the most climate-exposed pool. This is a pool that experiences the largest change in returns using current risk and using expected risk. Such pool includes areas of the urban-wildland interface of the Bay Area, including areas next to Cupertino, Saratoga, Los Gatos, and the greener areas west and east of San Martin.

Adapting to Wildfire Risk in 2050 and 2100: Does Risk Pooling help?

We can use the tools we develop to assess whether the ability to select mortgages for securitization helps in mitigating the impact of rising wildfire risk in the 21st century.

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 13, where the observations within the red dotted line are the in-sample simulations, and those right of the red dotted line are the forecasts. We use such global temperature deviations in combination with the coefficients of the wildfire propensity model estimated on Table 1 to forecast wildfire risk at the 5-digit ZIP code level in the future 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 and this is a Lucas critique. This paper focuses on one dimension of such Lucas critique, the evolution of MBS pooling and keeps other parameters constant.

[Figure 13 about here.]

Figure 14 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 metropolitan areas experience large increases, consistent with the finding that wildfires occur at the urban-wildland interface (Kestelman 2023).

[Figure 14 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 constant. We keep the 50 interest rate simulations 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 returns of MBSs.

[Figure 15 about here.]

The first finding is that the increased wildfire activity has an economically significant impact on expected returns, their standard deviation, and the Sharpe ratio as presented in Figure 15. Panel (d) of Figure 15 shows a scatter plot of the impact on each MBS's return (in %) by wildfire portfolio coefficient. Panels (a) and (b) of Figure 15 show the impact of rising risk in 2050 on expected returns and standard deviations. On the other hand, panel (c) of the figure shows the impact on the Sharpe ratio. These figures overall suggest that (i) wildfire risk can have an economically significant impact on returns but (ii) well diversified pools have very similar returns when originated now or in 2050.

The red lines of Figure 16 show the relationship between the Sharpe ratio and portfolio coefficients in 2050 (red) and with current risk (black line). Figure 16 shows the relationship between the Sharpe ratio and three portfolio coefficients: the portfolio for wildfire propensity, the portfolio coefficient for the interaction between wildfire propensity and household income, and the portfolio coefficient for the interaction between wildfire propensity and the FICO score. They suggest that the Sharpe ratio maximizing MBS may lower its allocation towards wildfire prone areas, *except* in places with high household income and high FICO scores.

[Figure 16 about here.]

6 The Pricing of Wildfire Risk in MBSs

Previous sections present evidence that mortgage cash flows and deal cash flows are affected by wildfire exposure. In particular, MBS experiencing correlated shocks may experience large increases in prepayments and losses.

Whether the impacts on cash flows, measured ex-post, are (i) reflected in the observed ex-ante prices of tranches and (ii) lead to ex-post changes in the returns of such tranches, remains an open question. There are indeed at least two separate questions: (i) whether investors price their expectations of wildfire exposure as the risk premium of a wildfire factor, and (ii) whether investors reprice MBS when learning new news about the wildfire risk of the unpaid principal balance of the deal.

We address point (i) by assessing how the sensitivity of each MBS deal's cash flows affect the *price level* of each tranche, as a compensating differential for the expected impact of wildfires on cash flows. We address point (ii) by estimating how such sensitivity affects the *returns* of each tranche, as increasing wildfire propensity leads to an adjustment of prices.

6.1 Measuring the Sensitivity (Beta) of Deal Cash Flows to Wildfire Risk

To assess the sensitivity of each deal's cash flow to wildfire risk, we need to use a deal-specific wildfire propensity factor. Section 2.2 provided a ZIP-level wildfire propensity factor with low type I and type II errors. Such factor, at the ZIP code $\times$ year level, based on temperature, land cover, drought, and electricity and road infrastructure maps, is a strong predictor of the local occurrence of wildfires. As MBS deals have mortgages in a large number of locations, we build an MBS wildfire propensity factor by dollar-weighting the wildfire propensity factors based on the unpaid principal balance in each location.

Correlating the MBS-level wildfire propensity factor with cash flows may not indicate a causal impact of wildfire risk probabilities on cash flows. Wildfires are located in specific places (e.g. the San Francisco Bay or specific neighborhoods of Los Angeles) that are also exposed to other economic factors. Our wildfire propensity factor could also be correlated with one of the 14 factors of Harvey & Liu (2021).

We estimate a heterogeneous, deal-level, sensitivity of cash flows to (a) the wildfire propensity factor, by controlling for a (b) deal fixed effect, which captures non-time varying differences in other climate risks such as flood risk, but also differences in economic factor exposure, and by controlling for (c) the short rate, the one-month T bill, (c) the term premium, measured either using the difference between the 5 year and the one month T-bill, or the difference between the 7 or 10-year Treasury and the one month T-bill. (b) and (c) capture the impact of interest rates on borrowers' prepayment and foreclosure behavior. Controlling for the term structure of interest rates is important as Table 6 suggests a significant pairwise correlation between the national dollar weighted wildfire propensity scores and the term premium, measured as in (c) above.

[Table 6 about here.]

The following regression is run separately, at the deal-level, along the time periods for which the cash flows of the deal are observed:

$$r_{dt}^{\mathrm{CF}} = \mathrm{Deal}_d + \beta_d^w \text{Wildfire PS}_{dt} + \beta_d^{1m} \text{One Month}_t + \beta_d^p \text{Term Premium}_t + \mathbf{x}_{dt} \beta_d^x + \varepsilon_{dt} \tag{20}$$

where β_d^w is the deal-specific sensitivity to wildfire risk, r_{dt}^{CF} is the monthly deal-level cash flow divided by the unpaid principal balance of the deal, Deal_d is a deal fixed effect. Later, we expand the analysis to the inclusion of fourteen additional factors. Here the Wildfire PS_{dt} is the deal-level wildfire propensity score, calculated as the dollar-weighted propensity score across locations of mortgages of the deal:

$$\text{Wildfire PS}_{dt} = \frac{\sum_{i=1}^{N_d} \text{Balance}_{idt} \text{Wildfire PS}_{\ell(i,d)t}}{\sum_{i=1}^{N_d} \text{Balance}_{idt}}. \tag{21}$$

The Balance_{idt} is the balance of mortgage i of deal d in month t, and Wildfire $\mathrm{PS}_{\ell(i,d)t}$ is the wildfire propensity for 5-digit ZIP code ℓ in month t. We use each of the four different propensity score measures PS0-PS3 developed in Section 2.2. This time-varying propensity score accounts for three types of variations: (i) the unequal timing of principal payments across locations, (ii) the geographic concentration of mortgage originations across locations within a deal, (iii) the evolution of the climate, including temperature extremes, land cover, and infrastructure. The wildfire propensity score is deal-specific j. This reflects the fact that deals differ in the geographic location of the mortgages at origination. However, the variation in the balance is only due to the prepayment of the principal or losses incurred.

We also allow for the possibility of additional controls $\mathbf{x}_{dt}$ specific to the pool, such as home price indices, home price appreciation, the state of the labor market, or the evolution of household size, as suggested by Davidson & Levin (2014), Fabozzi et al. (2011), and denoted by the letter gamma in Boyarchenko et al. (2019). These are drivers of mobility, and thus of prepayments and defaults. The term structure of interest rates is a major driver of MBS prices, as they determine the discounting of cash flows, the incentives to prepay and default, as well as correlate strongly with the 30-year fixed mortgage rate. The 30-year FRM correlates strongly with the 5-year and the 7-year Treasuries.

For each deal, the beta β_d^w w.r.t. wildfire propensity is thus a sufficient statistic for: the adaptation of the housing and the mortgage markets to natural disaster risk, as homeowners may have incentive to build more resilient units; in such a case wildfire exposure may not translate into an impact on deal-level cash flows CF_{jt}. The mortgage market may also adapt, as lenders may either offer the possibility of forbearance or the possibility of renegotiating the terms of the mortgage to avoid default. Thus, the β_j^w is a *reduced-form measure* of the adaptation of the housing and mortgage markets to natural disaster risk.

6.2 The Pricing of Wildfire Risk: MBS Bond Prices and the Repricing

MBS tranche prices should reflect the deal-specific sensitivity of cash flows w.r.t. wildfire risk if investors' forecasts of such sensitivity is consistent with our estimates of the wildfire cash flow beta.

In the second step of the Fama MacBeth approach, we estimate the cross-sectional correlation coefficients with prices or returns as the left-hand side, and with the estimated deal-level betas as explanatory variable. For each month t separately, we estimate γ_t^w:

$$\log p_{\tau dt} = \gamma_0 + \gamma_t^w \widehat{\beta}_{d(\tau)}^w + \gamma_t^{1\mathrm{m}} \widehat{\beta}_{d(\tau)}^{1\mathrm{m}} + \gamma_t^{\mathrm{p}} \widehat{\beta}_{d(\tau)}^{\mathrm{p}} + \eta_{dt} \tag{22}$$

where $\log p_{\tau dt}$ is the log price level of the tranche for 100 USD of notional. Results using the price level $p_{\tau dt}$ are qualitatively similar. $d(\tau)$ is the deal of tranche τ.

The $\widehat{\beta}_j^w, \widehat{\beta}_j^{1\mathrm{m}}, \widehat{\beta}_j^{\mathrm{p}}$ are generated regressors from the first step Fama MacBeth approach and thus the standard errors of $\hat{\gamma}^w$ require special treatment as described in an extensive literature . A variety of approaches are used in the literature (Shanken 1992, Goyal 2012, Petersen 2008). Here we estimate the variance covariance matrix of the estimates and estimate the variance of the average of the gammas accounting for the covariance across time periods. The variance-covariance matrix accounts for the Newey & West (1986) and Newey & West (1994) autocorrelation. Following Cochrane (2009), the average of cross-sectional risk premia for each month is equal to an estimate of the intertemporal risk premium:

$$\widehat{\gamma}^w = \frac{1}{T}\sum_{t=1}^{T} \widehat{\gamma}_t^w \tag{23}$$

And the standard errors of the average $\widehat{\gamma}^w$ account for the autocorrelation lags of the estimated risk premia $\widehat{\boldsymbol{\gamma}}^w$, as $\text{Var}(\widehat{\gamma}^w) = \frac{1}{T}\mathbf{e}'\Omega\mathbf{e}$, $\mathbf{e}$ is the vector of ones, and Ω is the variance-covariance matrix of the vector of monthly cross sectional estimates. Other approaches such as GMM and the Shanken correction are possible. Given the noisiness of the pricing of wildfire risk in tranches, we expect these tests to weaken the pricing further.

Are prices evolving as wildfire risk propensities increase? To answer this question, we estimate (24) using the log price changes as the dependent variable.

$$\Delta \log p_{\tau dt} = \zeta_0 + \zeta_t^w \widehat{\beta}_{d(\tau)}^w + \zeta_t^{1\text{m}} \widehat{\beta}_{d(\tau)}^{1\text{m}} + \zeta_t^{\text{p}} \widehat{\beta}_{d(\tau)}^{\text{p}} + \epsilon_{dt} \tag{24}$$

where ζ_t^w is the impact of the wildfire beta on the price return, $\zeta_t^{1\text{m}}$ is the impact of the 1-month T-bill return, and ζ_t^{p} is the impact of the term premium, as before.

6.3 Sample Construction: Tranche-Deal × Month Sample

The sample is built as follows. First, we consider the daily tranche price data set extracted using the Bloomberg Data Service described in Section 2.1. This provides a set of tranche prices at the level of the CUSIP and Bloomberg Identifier (BBGID). The frequency of the price data set is the month, consistent with the frequency of the cash flow data set. For each month, we keep the price of the tranche first observed, between January 2011 and February 2021. We choose to start in 2011 and exclude the data of the Great Financial Crisis where rates are volatile.[19] Prices are quoted per

[19] Delinquency rates on single-family residential mortgages peak in Q1 2011 and decline steadily until the end of the sample period (Series DRSFRMACBS). The 1-month T-bill does not exceed 1 percent between September 30th

100 USD of notional. We exclude outlier prices above 150 USD.[20] We consider tranches that have month-to-month price observations, which is the case for more than 99.9% of the tranche × month data, or 968,574 out of 969,456. We consider tranches for which month-to-month price changes do not exceed 50% in any month. These tranches are legacies of the great financial crisis and are experiencing fire sales in the early part of the sample. The 99th percentile of monthly price changes is +17.4% and the 1st percentile is −19.4%.

For each deal, we consider the set of tranches, ranked in order of their earliest observed price. The median number of tranches per deal is 7, and the average number of tranches per deal is 8.6. For all the deals in the tranche data set, we consider the cash flows due to prepayment and interest payment. Prepayment cash flows include unscheduled principal payments.

Second, we merge the tranche price panel data set at monthly frequency with the deal cash flow panel data set at the same frequency. Scheduled principal payments come from Corelogic variable `SCH_MNTH_P` and unscheduled principal payments are the decline in the balance over and above scheduled principal payments. This includes losses. Interest payments are computed using the current rate and the current balance, thus allowing for deals with ARMs and FRMs.

We estimate the betas of cash flows w.r.t. wildfire risk exposure at the *deal-level*. We estimate the pricing of risk for *each tranche separately*, allowing for heterogeneous pricing of cash flow risk depending on the seniority of the tranche within the deal. Apart from the ranking of tranches, this does not require further assumptions regarding the allocation of cash flows into tranches, as it treats deal-level cash flows separately from tranche-level prices. The longitudinal sample has two sets of key quantities at the deal- and the tranche levels. First, the deal-level cash flow return $\mathrm{r}_{dt}^{CF} = \frac{\mathrm{CF}_{dt}}{\mathrm{Balance}_{dt}}$ at monthly frequency, as the cash flow divided by the unpaid principal balance. Second, the deal-level price level $\log p_{\tau dt}$ and the log price change $\Delta \log p_{\tau dt}$ where τ is the tranche, d is the deal, and t is the month.

2008 and November 2017 (Series DGS1MO).

[20]The 99th percentile of the price distribution is 106.8 USD.

6.4 Estimation Results

Table 7 presents the impact $\widehat{\gamma}^w$ of the wildfire risk cash flow beta. Such $\widehat{\gamma}^w$ is estimated from the second stage of the Fama MacBeth regressions for a range of specifications. The dependent variable of the second step is the price level. Prior literature suggests the importance of robustness checks when estimating second-step regressions with generated regressors, and we therefore present estimates with 20 different regressions: (1) using all tranche prices (2) using only deals whose balance at origination is higher than 100 million dollars (3) for only the most junior tranches (tranche rank >0.5) (4) for the most senior tranches (tranche rank <0.5) and (5) for the most junior tranche only. We run each of these five specifications using the four different wildfire propensity scores (0,1,2,3) built in Table 1.

[Table 7 about here.]

Key facts emerge from this analysis. First, point estimates suggest that MBS tranche prices are lower when the sensitivity of cash flows to wildfire propensity is higher. This is consistent with the fact that MBSs experiencing prepayments and foreclosures during wildfires the point estimates are consistently negative, ranging between -0.19 and -1.631. Second, such impact is statistically significant for 15 of the 20 regressions. The result does not survive 5 of the specifications, those using the wildfire propensity score 0, which is a propensity score without controls (fixed effects) for local wildfire propensity. Third, while the difference is not statistically significant, the point estimates for junior tranches are larger than the point estimates of the risk premium of senior tranches. The point estimates for the most junior tranche are larger than the point estimates for the senior tranche. Overall, the data is suggestive of a pricing of wildfire risk, but cannot provide support in every tested specification.

Table 8 estimates whether greater wildfire risk propensities lead to greater returns $\Delta \log p_{\tau dt}$. Point estimates suggest that the most junior tranches experience the least amount of price changes: -0.004 insignificant for the most junior tranche in the first set of specifications, $+0.087$ for junior tranches (tranche rank > 0.5) as compared to $+0.165$ for senior tranches in the same set of specifications. This pattern holds when using the betas w.r.t. wildfire propensity scores 1, 2, or 3. When breaking down by tranche price rank at origination (Tranche rank >0.5 and Tranche rank <0.5), the results are significant in each of the 5 specifications (wildfire propensity 0,1,2,3).

[Table 8 about here.]

The estimates are significant at 95% for 10 of the 20 specifications. While this is suggestive, and while the sign of the point estimates are identical across specifications, it is not possible at this stage to conclude that tranche prices decisively price the wildfire propensity score.

6.5 Potential Confounders: Additional Pricing Factors and the Wildfire Propensity Factor as a "Zero-Beta" Factor

Our results on the pricing of wildfire risk exposure will be confounded if those wildfire risk factors are correlated with other common pricing factors. In this case, the beta w.r.t. to the deal-level wildfire risk factor would be capturing the correlation with an omitted variable. These omitted variables potentially include Fama & French's (2015) five factors, Frazzini & Pedersen's (2014) betting against beta, the gross profitability of Novy-Marx (2013), the liquidity of Pástor & Stambaugh (2003), the momentum factor of Carhart (1997), the quality minus junk of Asness, Frazzini & Pedersen (2019), investment and profitability from Hou, Xue & Zhang (2015), conditional skewness from Harvey & Siddique (2000), and common idiosyncratic volatility from Herskovic, Kelly, Lustig & Van Nieuwerburgh (2016). In total, we test for the potential confounding effect of 14 factors with each of the five potential wildfire risk factors at the national level:

$$\text{National Wildfire PS}_t = \frac{\sum_{j=1}^{J} \text{Volume Originated (USD)}_{jt} \text{PS}_{jt}}{\sum_{j=1}^{J} \text{Volume Originated (USD)}_{jt}} \tag{25}$$

where the 5-digit ZIP code wildfire propensity scores $j = 1, 2, \ldots, J$ are weighted by the dollar value of originations. An alternative is to weigh by the current outstanding balance in each 5-digit ZIP codes. For each propensity score $PS1$–$PS5$, and for each of the 14 factors, we estimate the correlation, e.g. $\text{Cor}(\text{PS}k_t, \text{smb}_t)$ for the smb factor. The absence of a significant correlation implies that the potential omitted variable bias is not significant.

The set of 5×14 pairwise correlations are presented on Table 9. The wildfire propensity factor is not significantly correlated at 1, 5 or 10% with the 5 Fama French factors. Out of the 70 pairwise correlations, only the correlations with the investment (ia) factor from Hou et al. (2015) are significant for each of the 5 wildfire propensity factors, with a significance level below 1% and above 5%.

[Table 9 about here.]

6.6 Investor Awareness: Textual Analysis of MBS Prospectuses

An analysis of the prospectuses of MBS deals may shed light on investors' awareness of wildfire risk, climate risk, and disasters. We collect the full text of 482 deals using a manual script on the Bloomberg terminal, and convert such prospectuses to series of words and expressions. Prospectuses contain a wealth of information on tranches, mortgages, coupons, and other factors. Here we focus on simple metrics: the occurence of words related to wildfire risk. This analysis can be extended with further metrics. Table 10 suggests that MBS prospectuses provide at least mention of wildfire risk beyond legal footnotes. We use two sets of words. First, we use the counts of 'wildfire' and 'wildfires'. Second, we use the Merriam-Webster thesaurus to build a set of words related to wildfires, hurricanes, climate change (29 words in this analysis).

[Table 10 about here.]

The results are presented on Table 10. Rows 1 and 3 present the frequency of words per 100,000 words, and rows 2 and 4 present the simple count of words per deal. Table 10 presents the moments of the distribution, where each observation is an MBS deal. The average prospectus mentions the word wildfire or wildfires 0.6 times per 100,000 words, and 1.02 times in a prospectus. The 90th percentile of the distribution mentions the word wildfire 2.21 times per 100,000 words, and 4 times overall. When using a broader set of words (list on the table), the average is significantly higher, at 14.79 times per 100,000 and 23.58 times overall.

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 risks 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, as quantified in Table 5, 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, across the nation, and then across countries, makes the financial system more resilient.

Mortgages are light to 'ship to pools' across the nation and countries;[21] 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 a flat assessment of probabilities. In the growing market for climate risk assessments, spurred by the SEC's new climate change disclosure rules, investors and regulators alike can acknowldege the benefits of assessing portfolio correlations as those drive risk over and above average risk probabilities.[22]

[21] For the impact of wildfires in Portugal on mortgage pricing, see Götz, Mager & Zietz (2024).
[22] "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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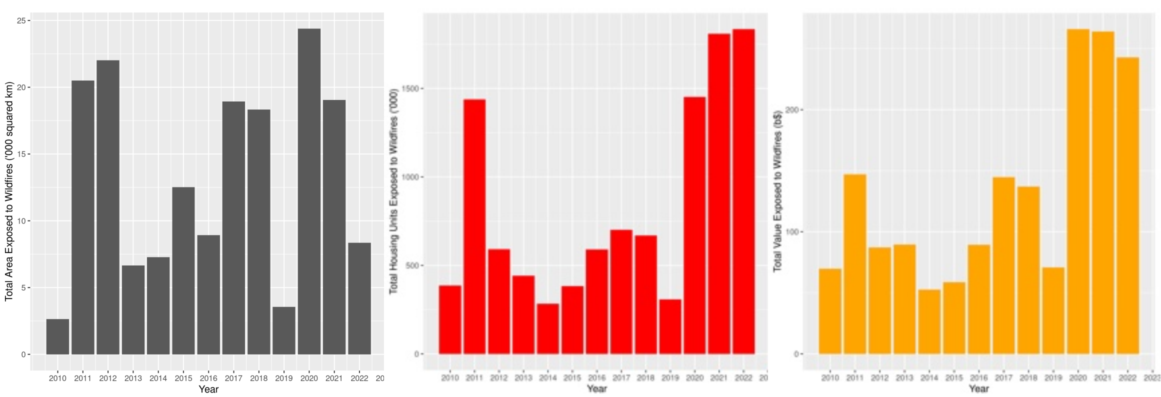
Figure 1: Rising Wildfire Frequency – Surface Area of Wildfire Perimeters, Housing Units and Total House Value Affected

These three charts present the annual exposure to wildfires by (a) surface area, (b) the number of housing units, (c) housing value. The surface area exposed is in thousands of squared 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) Surface Area Exposed **(b)** Housing Units Exposed **(c)** Housing Value Exposed



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

Figure 2: Rising Spatial Correlations in Wildfire Risk

These three barplots present the spatial correlation across 5-digit ZIP codes in wildfire occurrence. For each year t, we consider a time window $[\![t-2..t+2]\!]$ of two years before and after, and estimate the correlation across ZIP codes over these five years. The correlation is either in the share of the surface affected (a), in the share of housing units affected (b), or in the share of housing value affected (c). The share in (a) is the spatial intersection of wildfire perimeters with ZCTA5 boundaries. The shares in (b) and (c) are obtained by intersecting wildfire perimeters with Census tract data for 2010. As such, it keeps the distribution of housing units and their values constant.

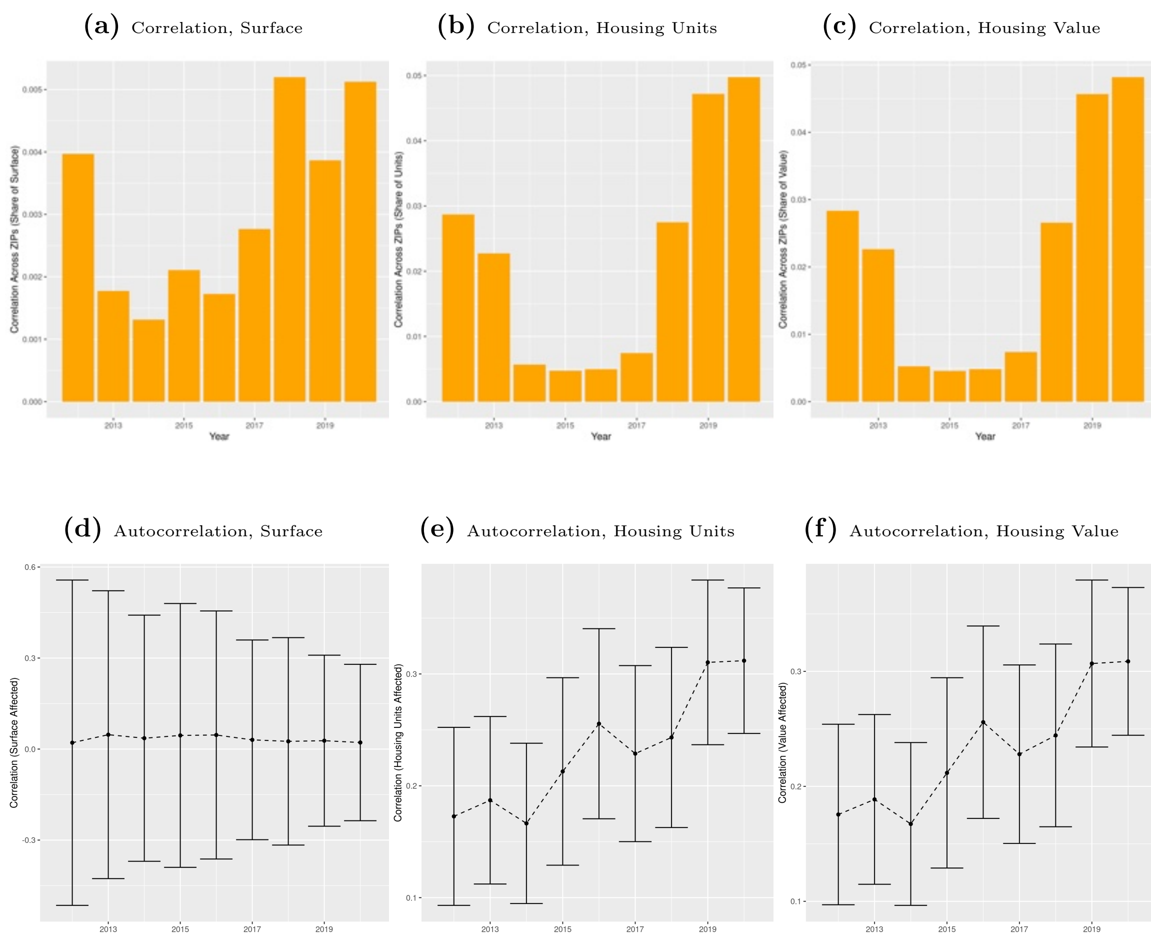
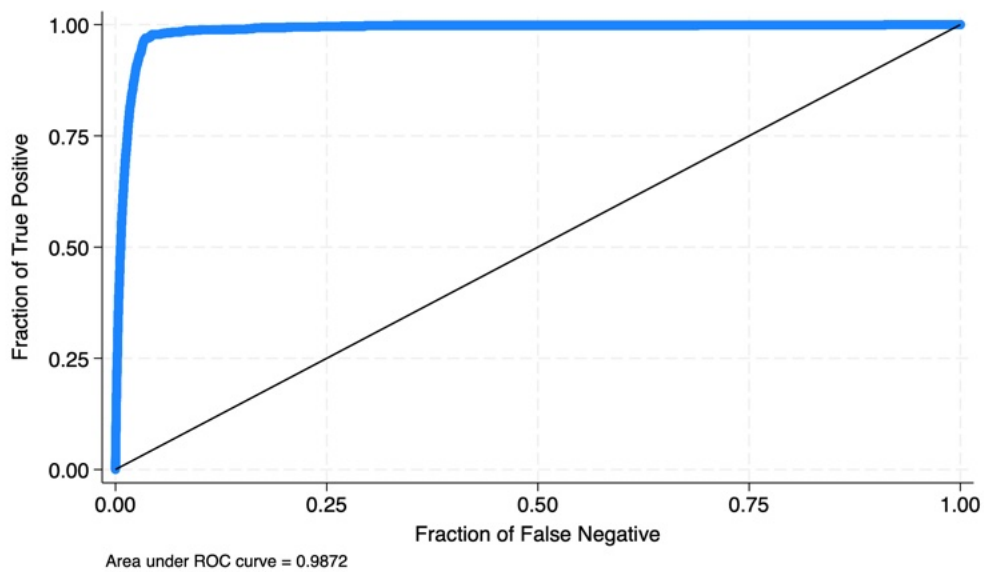


Figure 3: Wildfire Propensity Score – Out-of-Sample ROC Curves: Performance of Wildfire Propensity Regressions

The figure presents the out-of-sample ROCs for the logistic regressions of PS0 and PS3 from Table 1 regressed until 2019. The out-of-sample ROCs are estimated for 2020 and 2021.

(a) Out-of-Sample ROC of PS0 (No Fixed Effects)



(b) Out-of-Sample ROC of PS3 (with Fixed Effects)

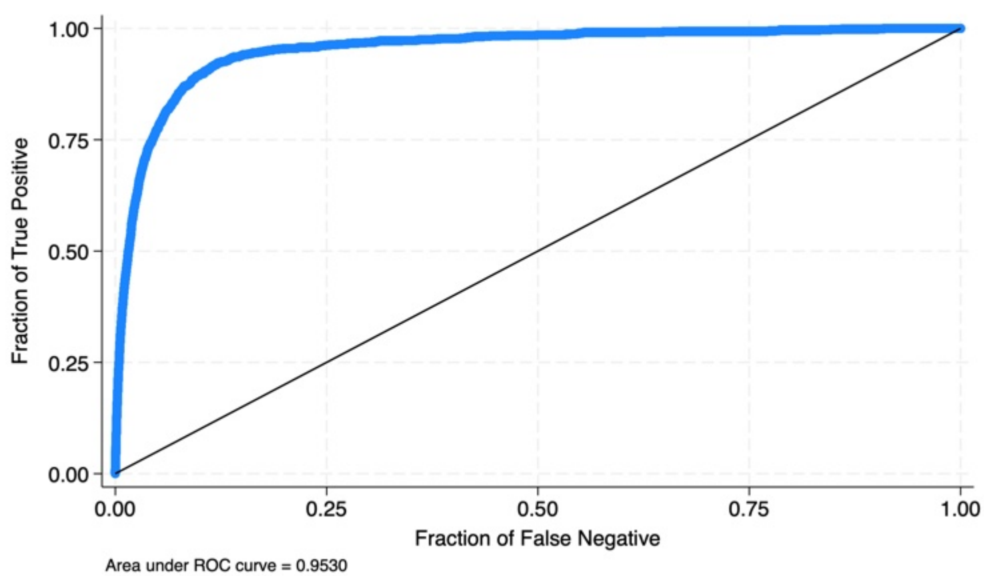
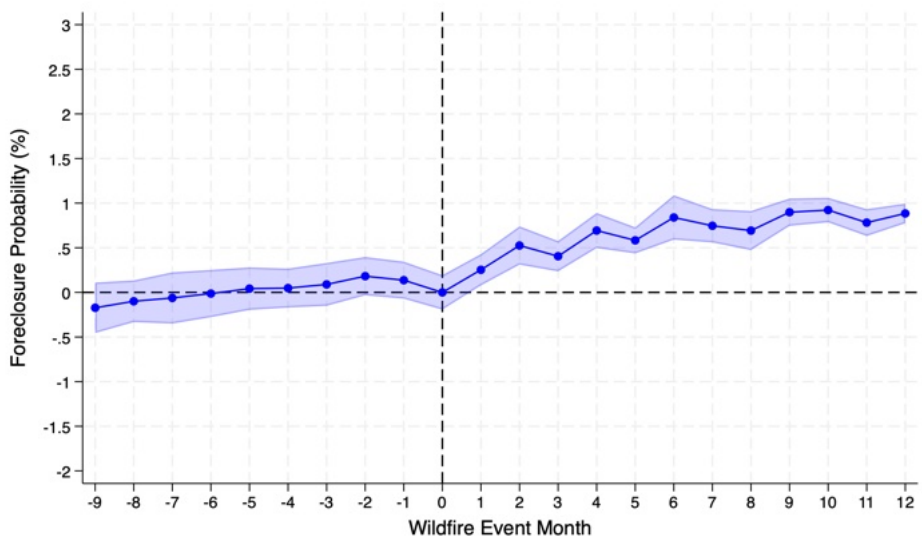


Figure 4: Mortgage-Level Analysis – Wildfire Exposure and Mortgage-Level Cash Flows

The figures present the two-way DiD regression of the likelihood of foreclosure (panel (a)) and prepayment (panel (b)) using equation (2). The 90% confidence intervals are presented for the event study from -9 months and $+12$ months around a wildfire event. Robust standard errors are clustered by mortgage and year-month.

(a) Two-Way Fixed-Effects DiD Estimation of Wildfires on Foreclosure



(b) Two-Way Fixed-Effects DiD Estimation of Wildfires on Prepayment

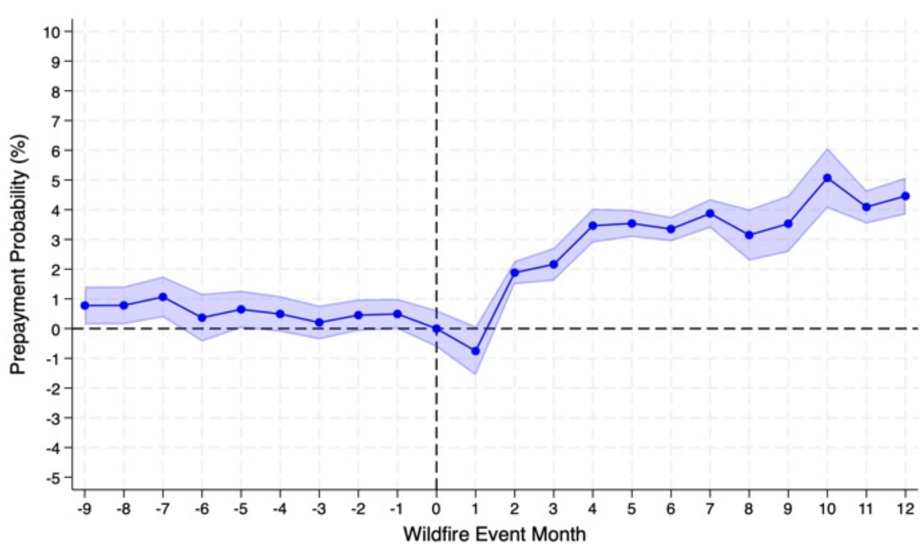
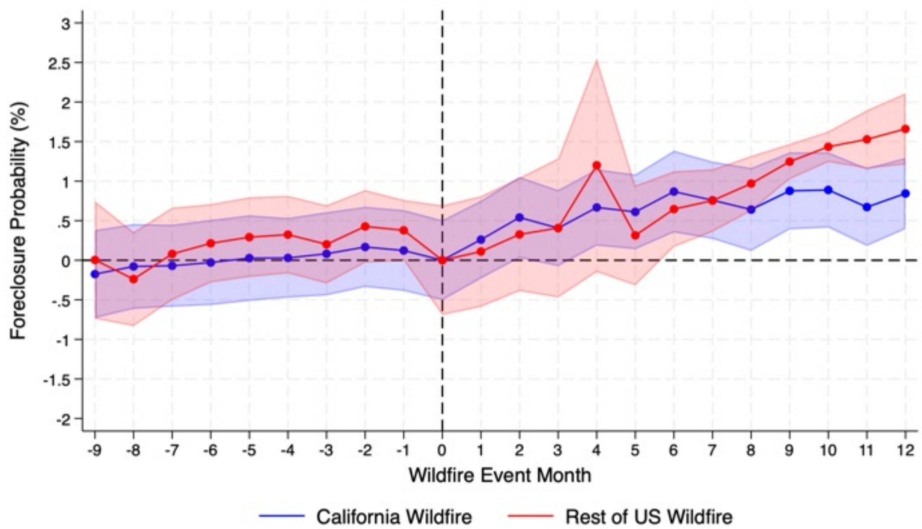


Figure 5: Mortgage-Level Analysis – Wildfire Exposure and Mortgage-Level Cash Flows by Location

The figures present the two-way DiD regression of the likelihood of foreclosure (panel (a)) and prepayment (panel (b)) using equation (2). The 90% confidence intervals are presented for the event study from −9 months and +12 months around a wildfire event. Robust standard errors are clustered by mortgage and year-month. In both panels, the interaction between wildfire event dummy and event month dummies are also interacted by a California dummy to present the event results on California wildfires and rest of the US wildfires, separately.

(a) Two-Way Fixed-Effects DiD Estimation of Wildfires on Foreclosure



(b) Two-Way Fixed-Effects DiD Estimation of Wildfires on Prepayment

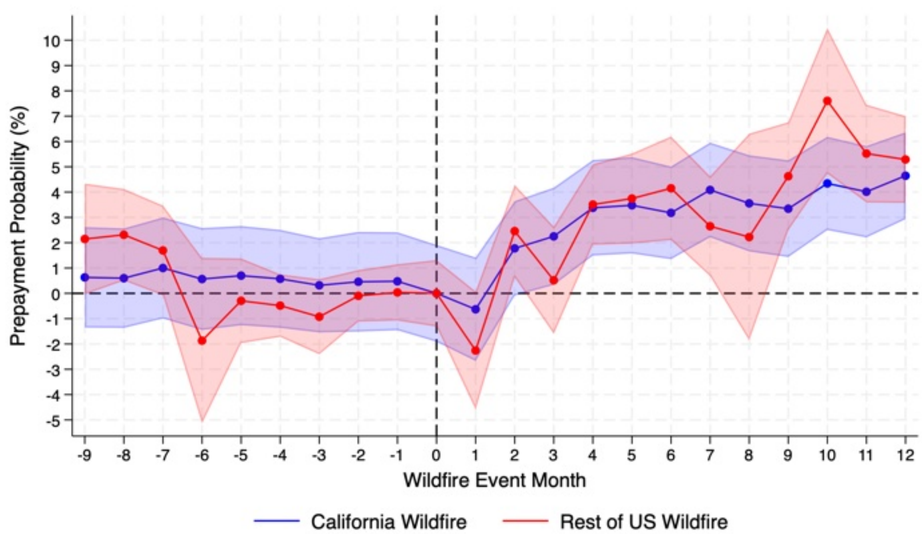
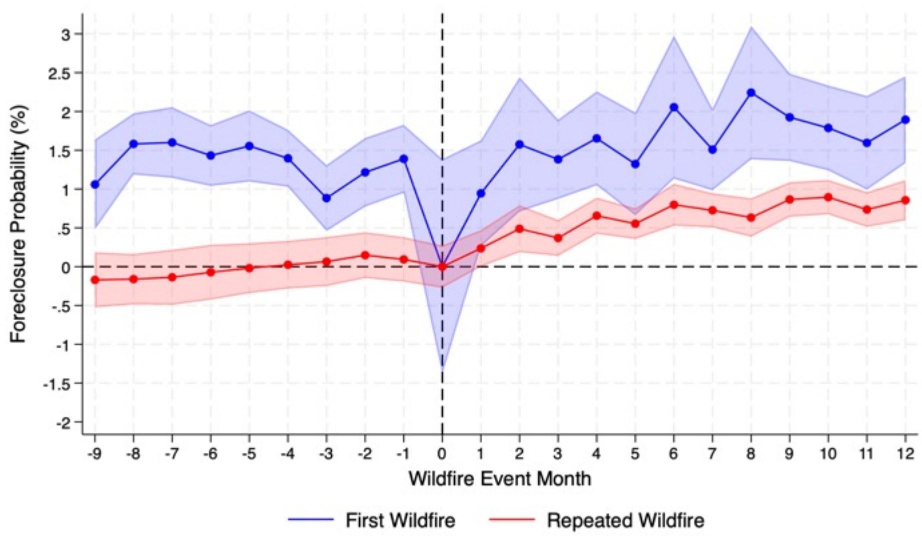


Figure 6: Mortgage-Level Analysis – Wildfire Exposure and Mortgage-Level Cash Flows by Timing

The figures present the two-way DiD regression of the likelihood of foreclosure (panel (a)) and prepayment (panel (b)) using equation (2). The 90% confidence intervals are presented for the event study from −9 months and +12 months around a wildfire event. Robust standard errors are clustered by mortgage and year-month. In both panels, the interaction between wildfire event dummy and event month dummies are also interacted by a first wildfire (in a ZIP code) dummy to present the event results on the first wildfires and repeated wildfires, separately.

(a) Two-Way Fixed-Effects DiD Estimation of Wildfires on Foreclosure



(b) Two-Way Fixed-Effects DiD Estimation of Wildfires on Prepayment

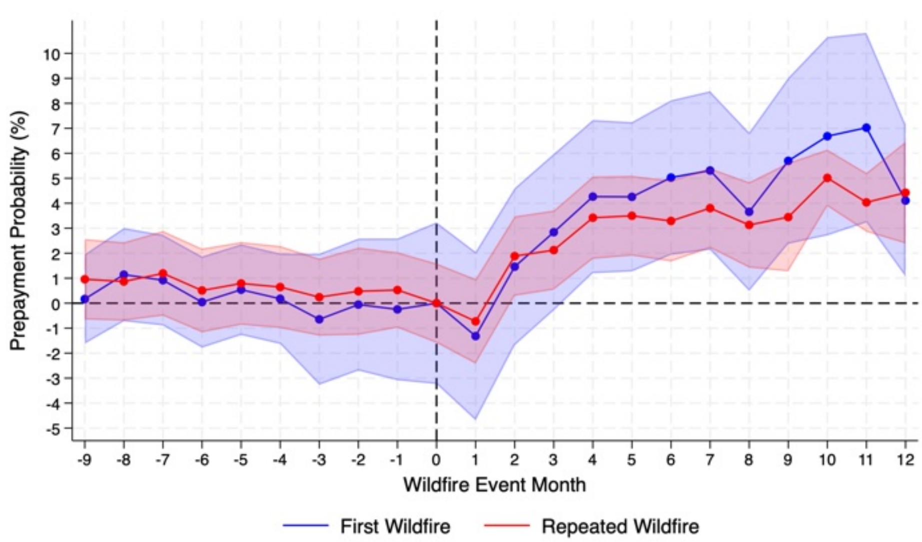
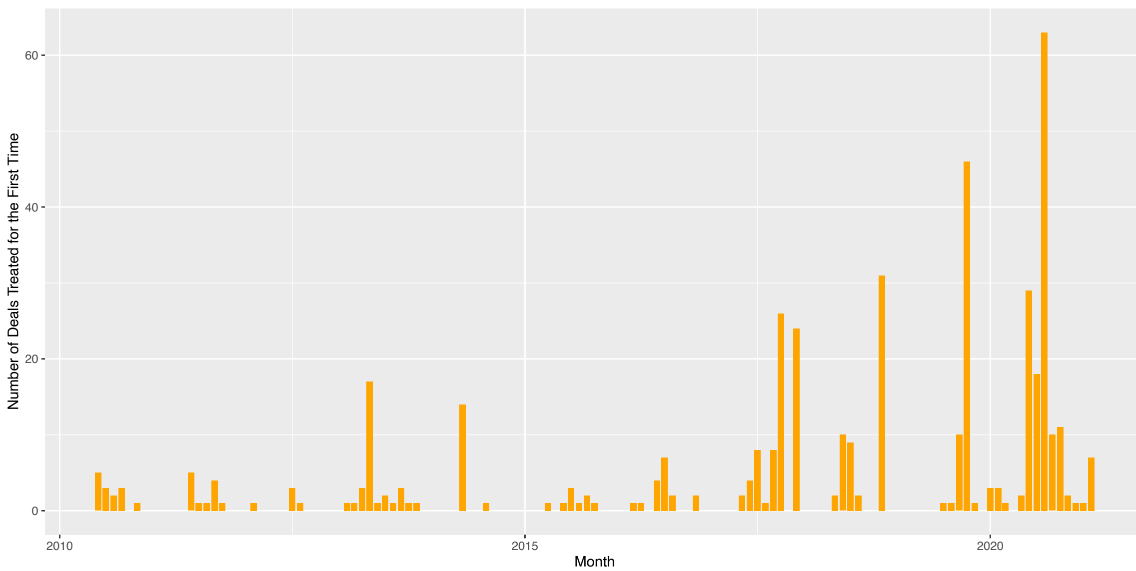


Figure 7: MBS Deal Analysis – The Exposure of MBS to Wildfires – Event Study Design

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

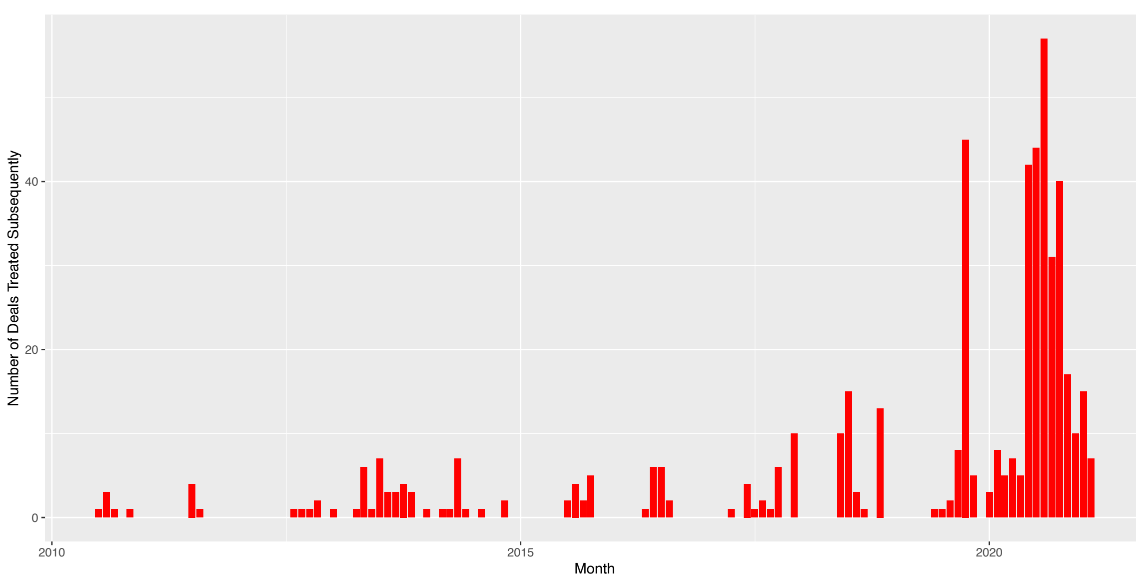
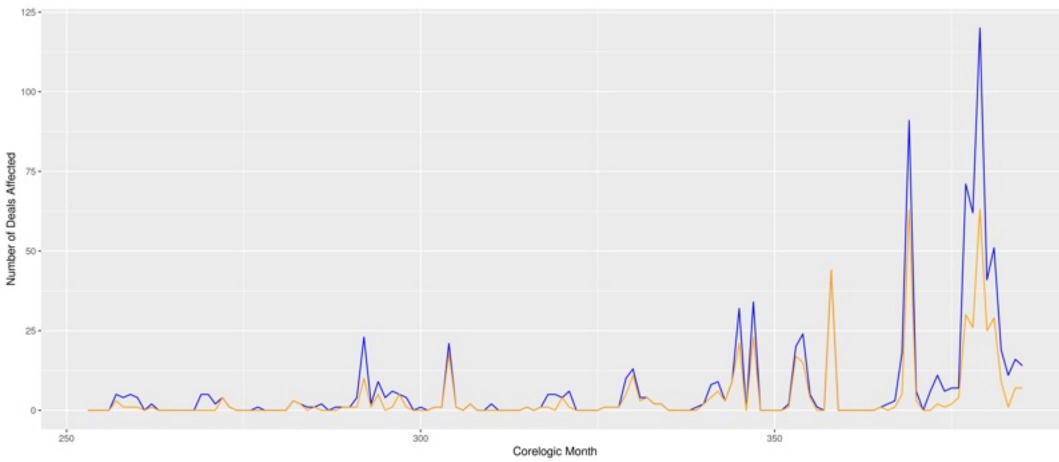


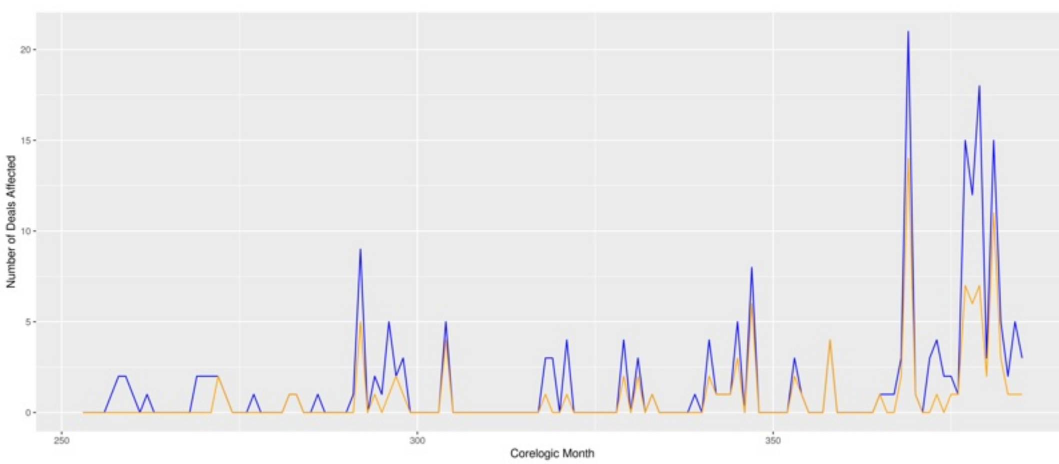
Figure 8: MBS Deal Analysis – The Exposure of MBS to Wildfires – At Different Thresholds

The three panels present, across months, the number of MBS deals exposed by share of the UPB in treated ZIPs. A deal is in the treatment group when the treated ZIP codes represent more than 5% of the unpaid principal balance of the deal on panel (a), 10% on panel (b), and 15% on panel (c).

(a) Number of Deals with more than 5% Affected (Dollar Value Measure)



(b) Number of Deals with more than 10% Affected (Dollar Value Measure)



(c) Number of Deals with more than 15% Affected (Dollar Value Measure)

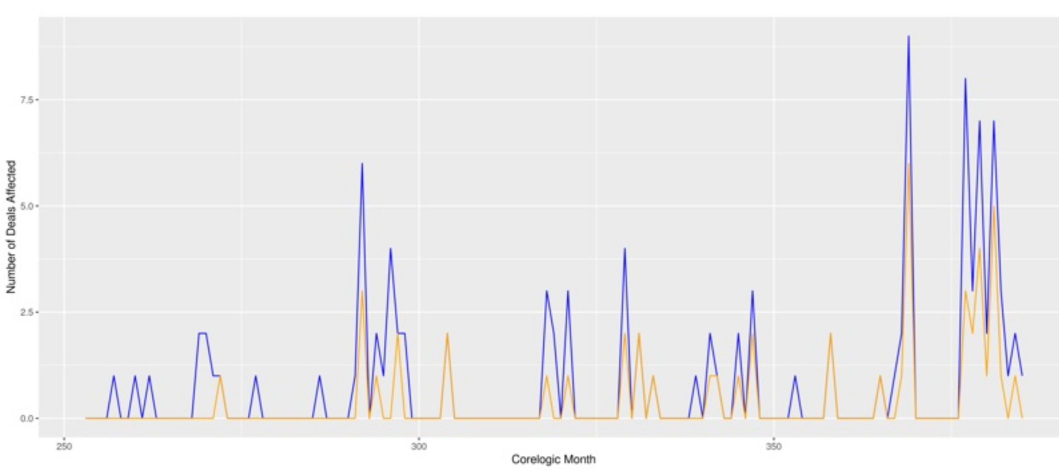
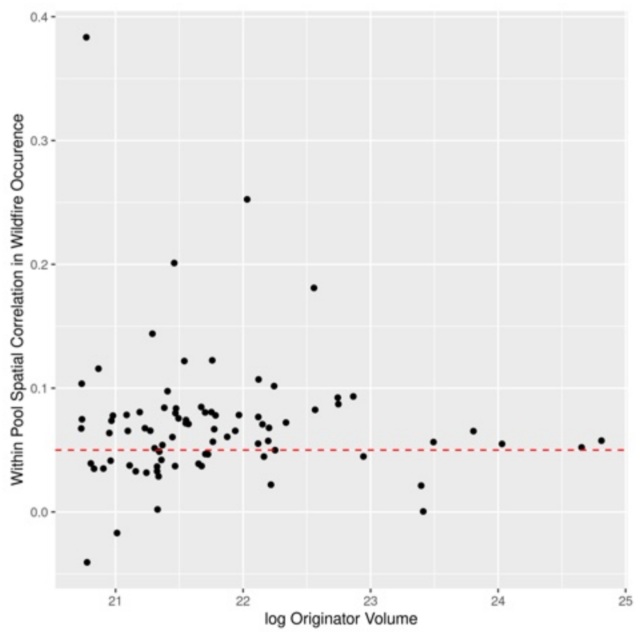


Figure 9: MBS Deal Analysis – Within-MBS Spatial Correlation in Wildfire Risk

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

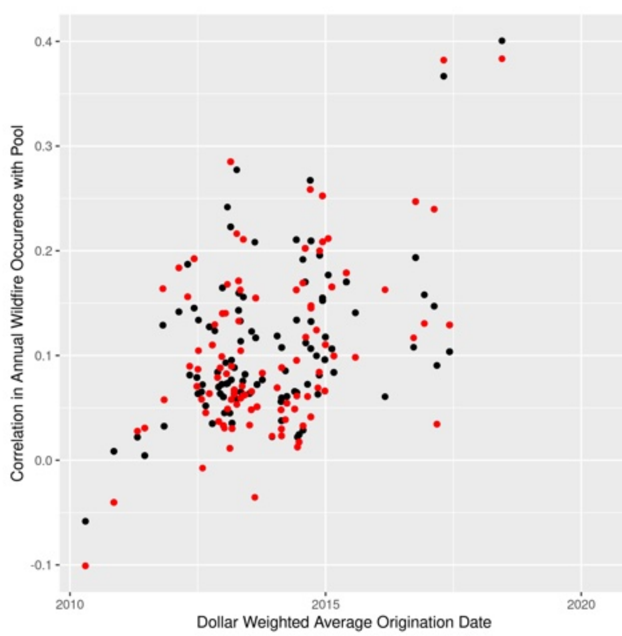
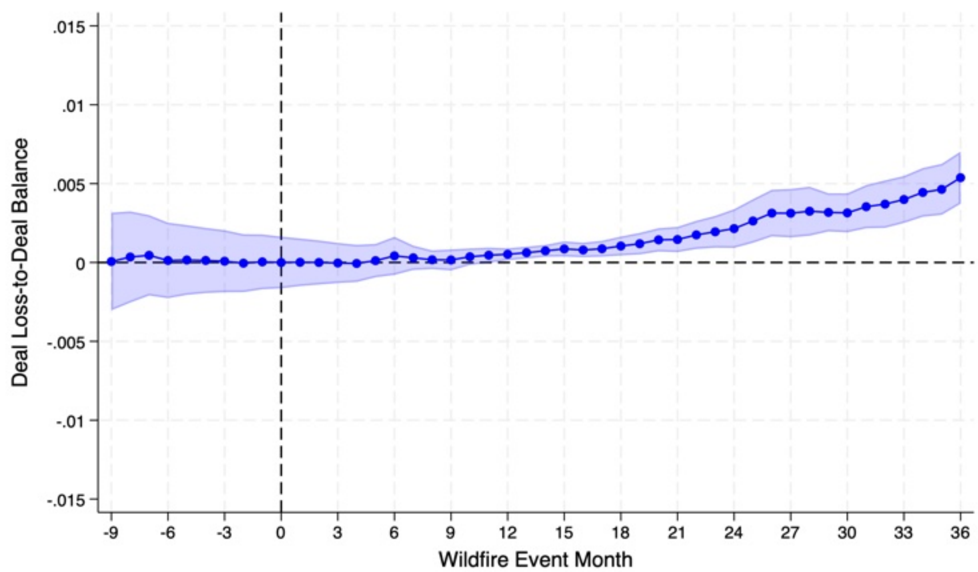


Figure 10: MBS Deal Analysis – The Impact of Wildfires on Deal Cash Flows – Event Study Design

The figures present the two-way DiD regression of deal-level loss normalized by unpaid balance in a deal using equation (12). Panel (a) presents the event study results where deals are treated when the deal is affected by more than 2% of the unpaid balance at the time of the first wildfire. Panel (b) presents the event study results where deals are treated when the deal is affected by more than 5% of the unpaid balance at the time of the first wildfire. Control group includes unaffected deals and the deals that are affected by less than 1% of the unpaid balance at the time of a treated wildfire. The 90% confidence intervals are presented for the event study from −9 months and +36 months around a wildfire event. Robust standard errors are clustered by deal and year-month.

(a) Deals Affected by at least 2% of Deal Balance



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

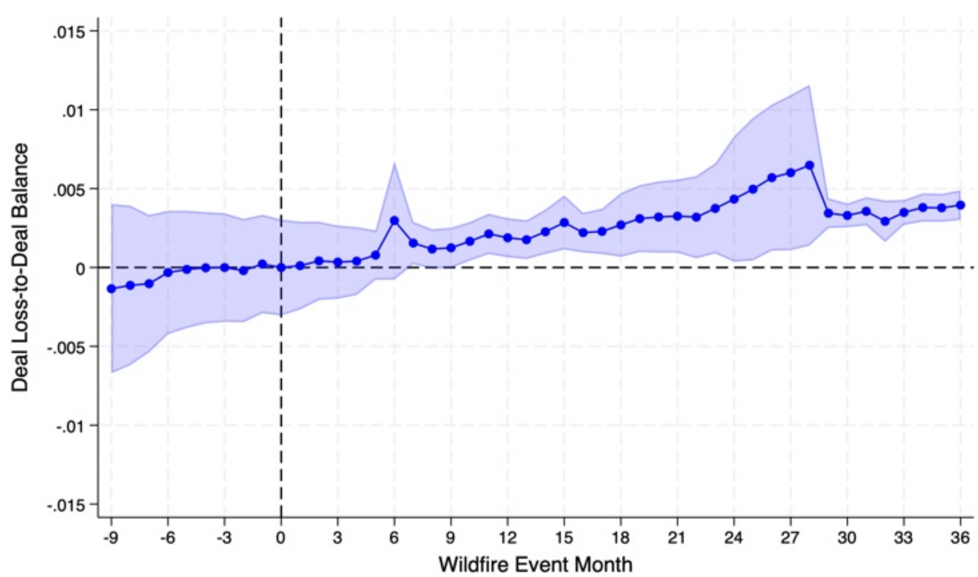
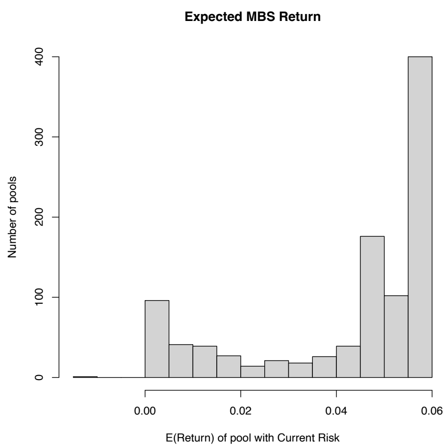


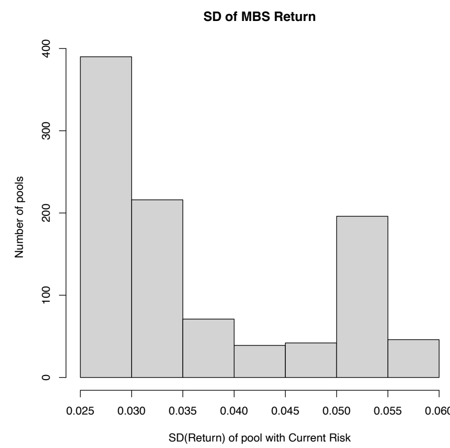
Figure 11: Designing MBS – Simulated Pools and their Performance

We simulate the cash flows of 1,000 pools with different geographic diversification coefficients (portfolio coefficients ω^w and $\boldsymbol{\omega}$), and across 50 different simulations of interest rate paths and wildfire shocks for each pool, over 360 months. The upper left graph shows the distribution of average monthly returns across deals. The vertical axis is the number of pools, the horizontal axis is the expected monthly return (0.06=6%). The upper right histogram shows the distribution of MBS-level standard deviation of returns. Panel (c) presents the distribution of the sharp ratio of the simulated pools. Panel (d) focuses on one MBS, that which maximizes the Sharpe ratio of monthly returns. The panel shows one point per 5-digit ZIP code where the MBS deal includes mortgages. on the vertical axis, the dollars originated in each location. On the horizontal axis, the wildfire propensity score. The Sharpe ratio maximizing MBS features non-zero weights on wildfire exposed areas.

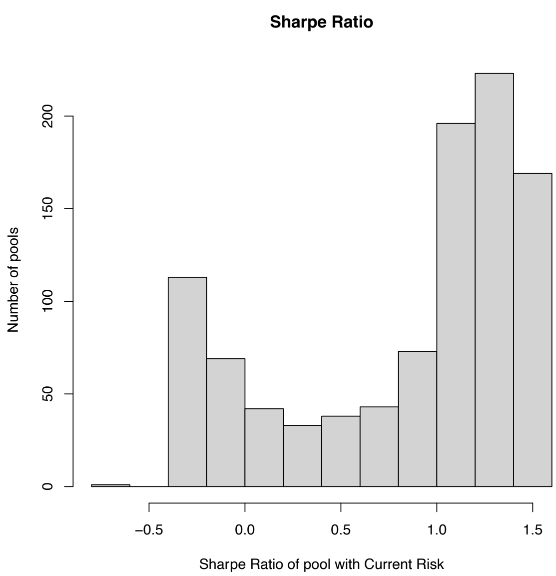
(a) Baseline Distribution of E(Returns) Across Simulated MBSs



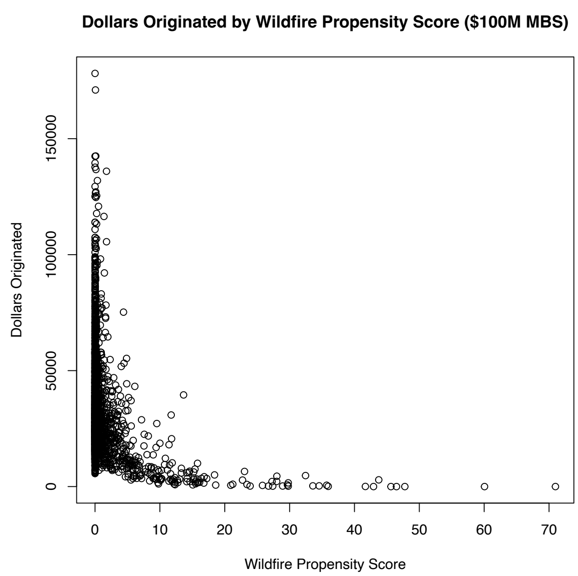
(b) Baseline Distribution of SD(Returns) Across Simulated MBSs



(c) Baseline Distribution of Sharpe Ratios Across Simulated Pools



(d) Dollars Invested by Location for the Sharpe Ratio Maximizing MBS



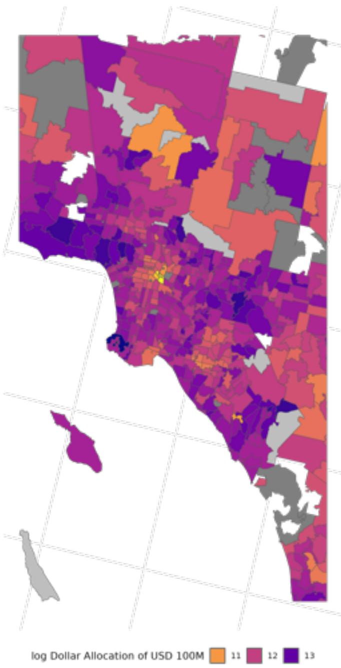
Source: Simulations by the authors. ZIP-level cash flows calculated using the historical ZIP-level prepayment and foreclosure rates. Impact of wildfires on cash flows estimated on Figure 4. Wildfire frequencies and within-state spatial correlations across ZIP codes estimated using National Fire Interagency data.

Figure 12: Designing MBSs – Sharpe Ratio Maximization and Resilience to Climate Change

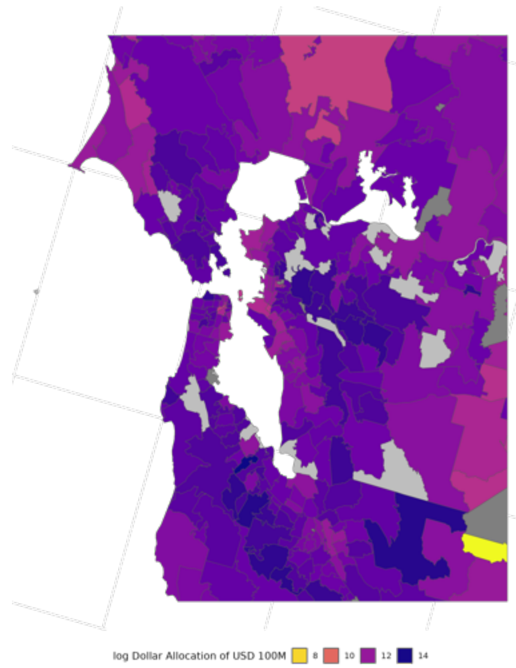
The bottom panel plots the dollar allocation of mortgage originations at the mean-variance-maximizing portfolio. ω^w *is the coefficient of wildfire propensity in the (Koijen & Yogo 2019) portfolio weight.*

— Designing Deals: Sharpe-Ratio Maximizing —

(a) Los Angeles

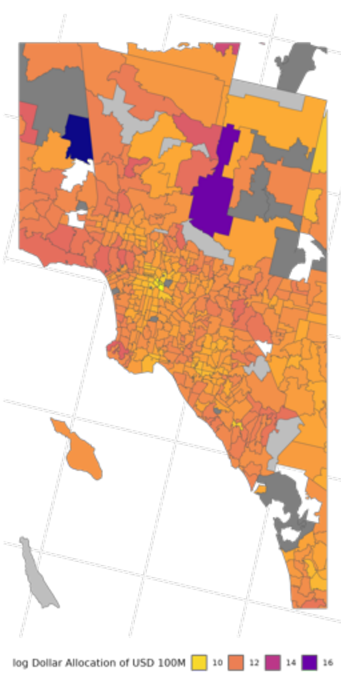


(b) San Francisco



— Designing Deals: Returns Most Affected by Rising Temperatures —

(c) Los Angeles



(d) San Francisco

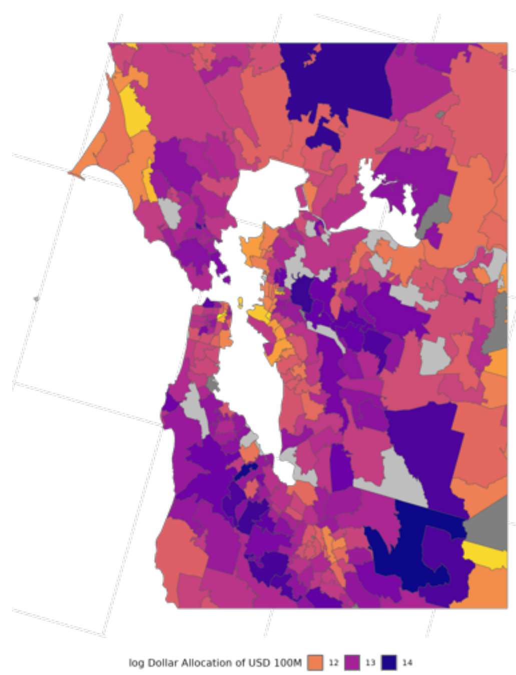


Figure 13: Designing MBS Deals with Evolving Risk – Global Surface Temperature Forecasts

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. The red dotted lines are for the in-sample data used in the MBS simulations.

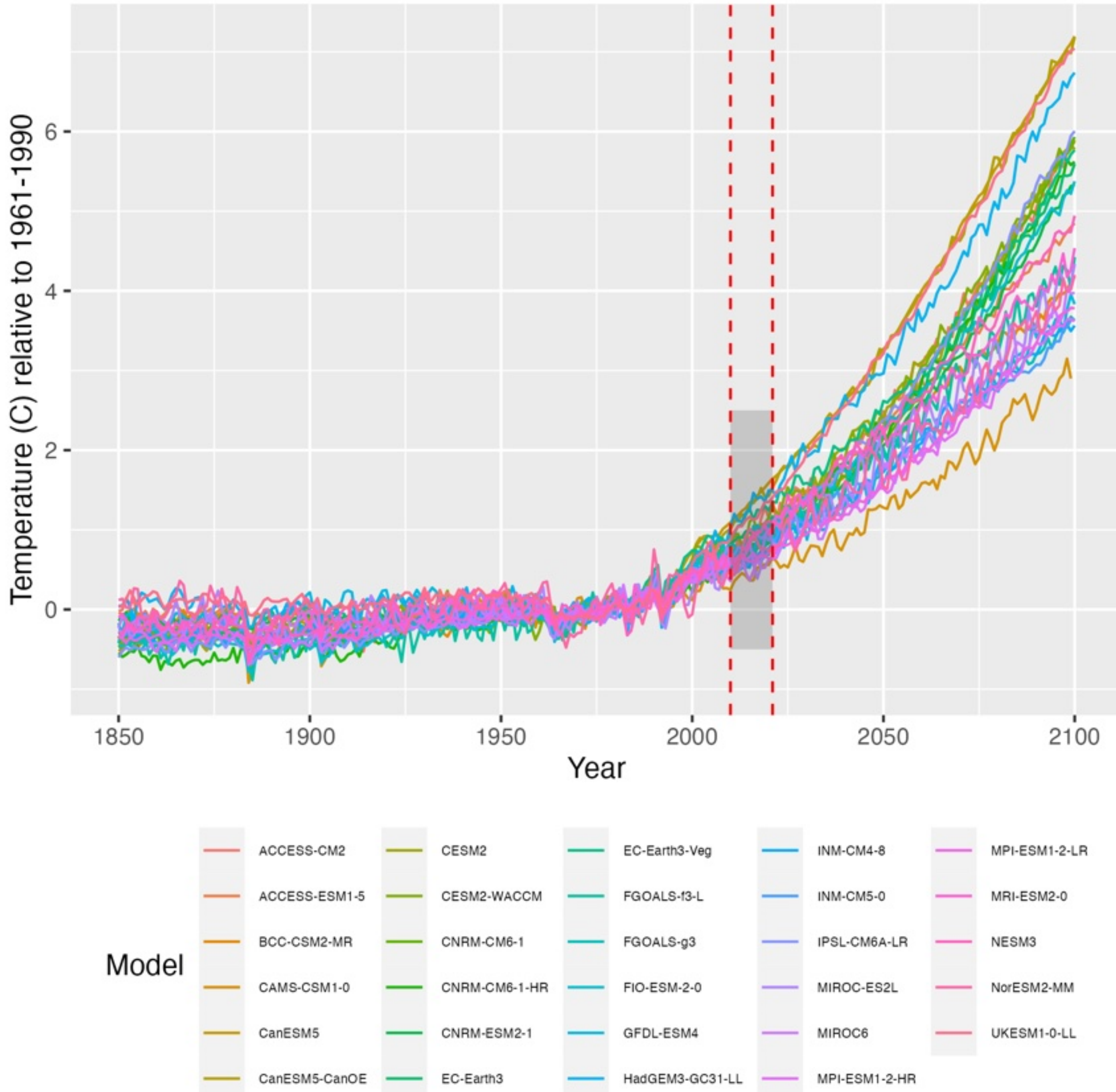
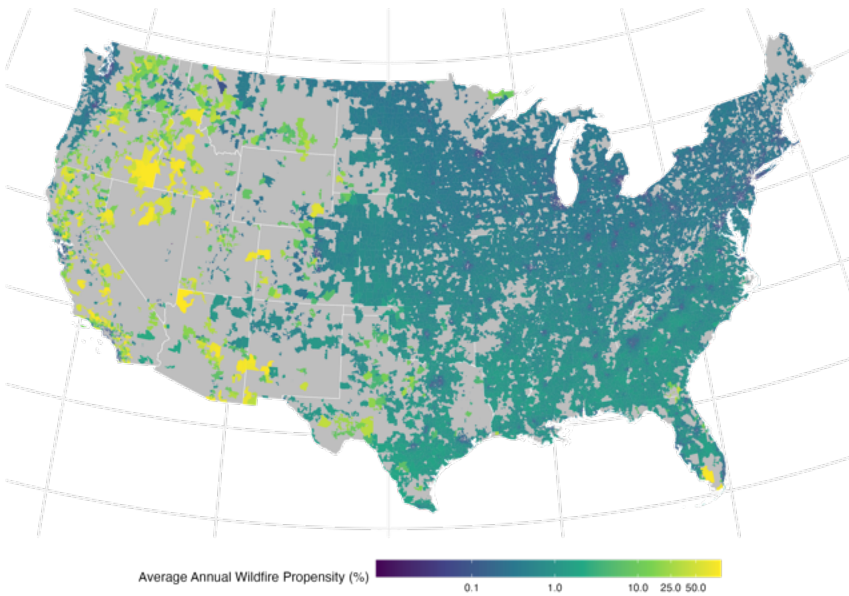


Figure 14: Designing MBS Deals with Evolving Risk – Evolution of the Wildfire Propensity Score

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)

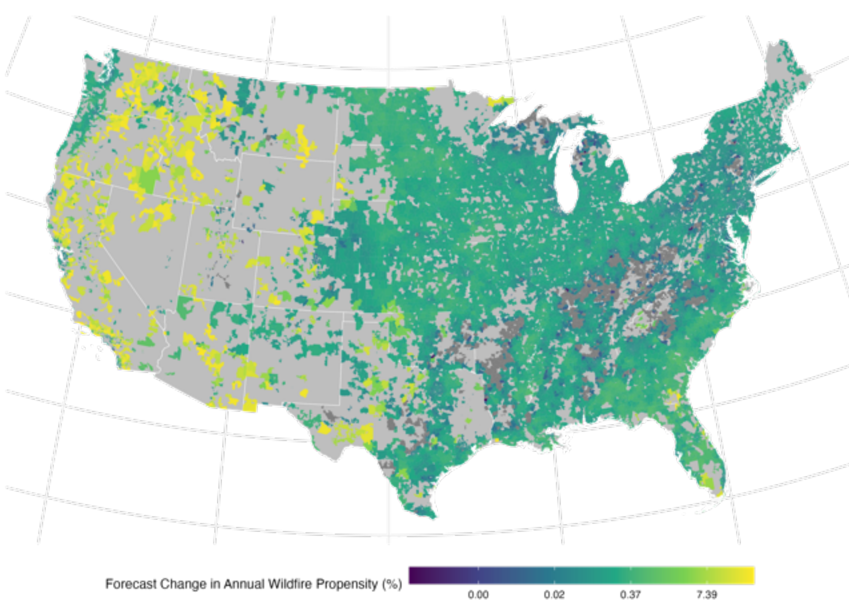
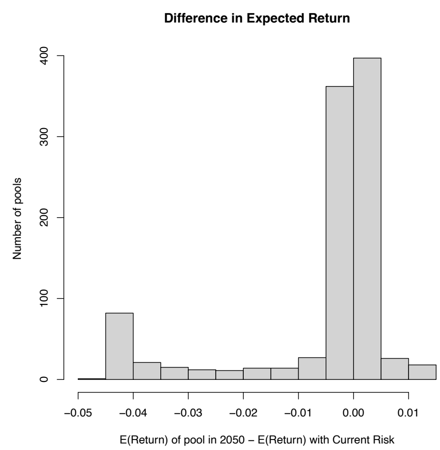


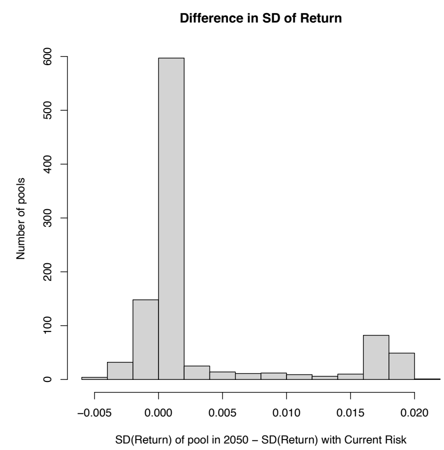
Figure 15: Designing MBS – Simulated Pools and their Performance, with Rising Temperatures

Across 1,000 simulated MBS pools as in the previous Figure, the two upper panels show the impact of rising temperatures, and thus rising wildfire risk, on expected returns (a) and the standard deviations of returns (b). Panel (c) shows the impact of rising wildfire risk in 2050 on portfolios with different weights ω^w *on the wildfire propensity score. Panel (d) relates the change in return by 2050 based on rising temperatures to the portfolio coefficient of wildfire risk.*

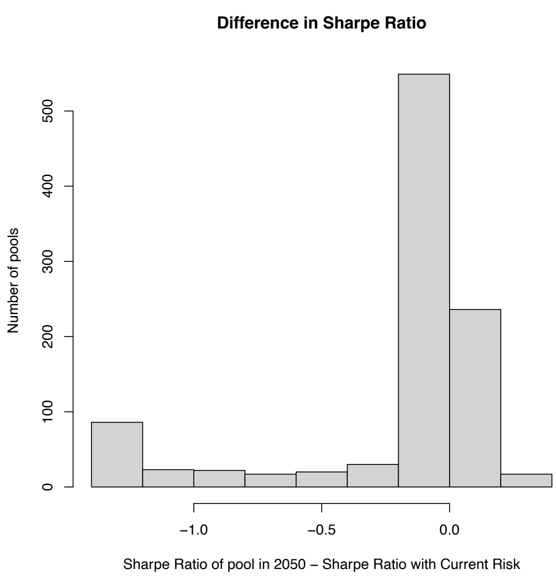
(a) Impact of Rising Temperatures on E(MBS Returns)



(b) Impact of Rising Temperatures on SD(MBS Returns)



(c) 2050-Now Evolution of Pool-Level Sharpe Ratios



(d) Change in Expected Return by Wildfire Weight in Portfolio, Now to 2050

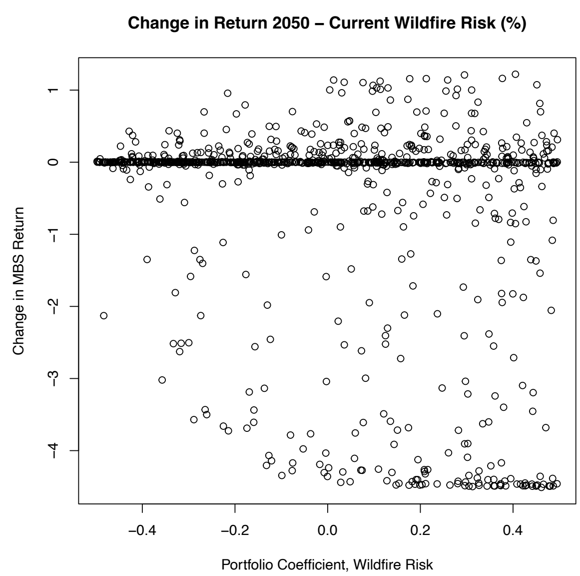
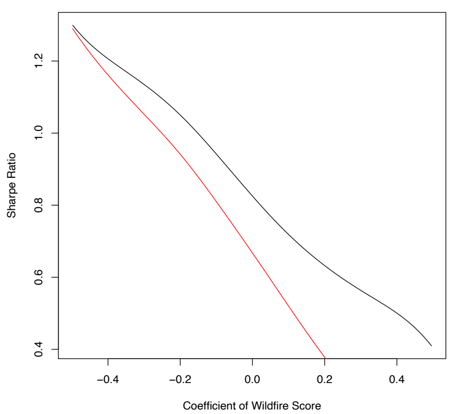


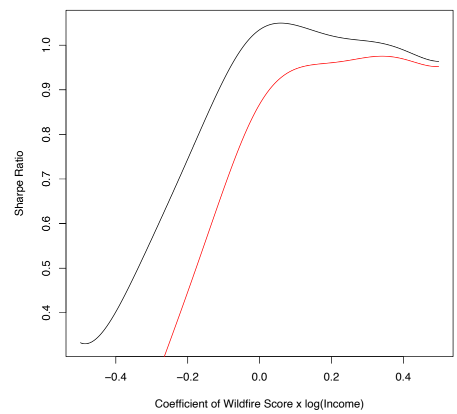
Figure 16: Designing MBSs – Portfolio Coefficients and MBS Sharpe Ratio with Current Wildfire Risk (Black) and with Wildfire Risk in 2050 (Red)

These graphs show the relationship between the Sharpe ratio of monthly MBS returns and the portfolio coefficients. As in Koijen & Yogo (2019), the portfolio weight is pinned down by a discrete choice model as in McFadden (1974). Here the covariates are the zip-level wildfire propensity score (as in Table 1), the median household income from the 2010 Census, the average FICO score, the interaction between the wildfire propensity score and household income, and the interaction between the wildfire propensity score and the FICO score. The zip code-level covariates pin down the allocation of mortgage origination dollars.

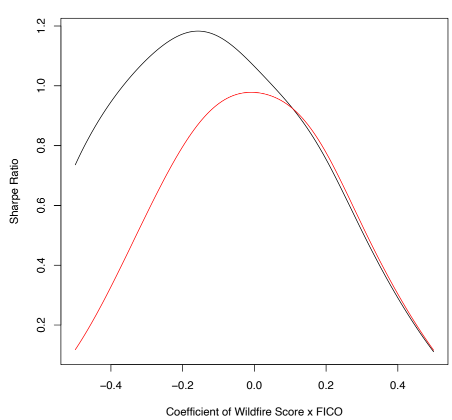
(a) Sharpe Ratio and Portfolio Coefficient for Wildfire Propensity Score



(b) Sharpe Ratio and Portfolio Coefficient for the interaction between Wildfire Propensity Score and Median Household Income



(c) Sharpe Ratio and Portfolio Coefficient for the interaction between Wildfire Propensity Score and FICO



—: wildfire risk using 2010-2021 data. —: wildfire risk using projected IPCC CMIP6 temperature in 2050, and the wildfire logit coefficients estimated on Table 1.

Table 1: Wildfire Propensity Score – Estimation of the 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 state-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	0.229***	0.266***	0.265***	0.262***
	(0.009)	(0.011)	(0.011)	(0.011)
Mean Temperature	0.106***	0.062***	0.063***	0.062***
	(0.003)	(0.013)	(0.013)	(0.013)
ln(Drought Index)	0.036***	0.101***	0.051***	0.049***
	(0.011)	(0.007)	(0.009)	(0.009)
× Forest Share	0.003***		0.002***	0.002***
	(0.000)		(0.000)	(0.000)
Forest Share	-0.005***	0.003**	-0.006***	-0.007***
	(0.002)	(0.001)	(0.002)	(0.002)
Developed Area Share	-0.009**			-0.018***
	(0.004)			(0.006)
Electricity Lines (m/m2)	226.911**			357.312***
	(105.138)			(135.263)
Road Length (m/m2)	-72.807**			32.666
	(34.382)			(46.157)
ln(ZIP Code Area)	0.222***	0.828***	0.831***	0.773***
	(0.027)	(0.032)	(0.032)	(0.038)
ln(# of State-Level Past Wildfires)	2.098***			
	(0.031)			
Constant	-13.894***	-24.565***	-24.449***	-23.292***
	(0.560)	(0.704)	(0.703)	(0.822)
Year FE	–	Yes	Yes	Yes
Month FE	–	Yes	Yes	Yes
State FE	–	Yes	Yes	Yes
# of ZIP Code-Months	5,396,580	3,205,692	3,205,692	3,205,692
In-Sample ROC	0.984	0.969	0.969	0.969

Table 2: 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					
	(1)	(2)	(3)	(4)	(5)	(6)
Wildfire (1=Yes)	0.052***	0.063***	0.045*	0.038	6.156***	7.033***
	(2.597)	(2.679)	(1.784)	(1.550)	(3.853)	(3.931)
× ln(FICO)					-0.929***	-1.061***
					(-3.818)	(-3.887)
ln(FICO)				-0.652***	0.061*	0.071**
				(-3.356)	(1.905)	(2.566)
Selection Correction		-0.000	0.000	0.000	0.000	-0.000
		(-0.633)	(0.108)	(0.233)	(0.262)	(-0.635)
ln(Unpaid Balance)			0.045***	0.061***	0.065***	0.065***
			(2.946)	(4.992)	(5.604)	(4.570)
Adjustable (1=Yes)			-0.127***	-0.097***	-0.085***	-0.074***
			(-5.288)	(-5.827)	(-5.239)	(-4.421)
ln(Term to Maturity)			0.279***	0.297***	0.295***	0.320***
			(8.952)	(10.356)	(11.142)	(10.481)
LTV (%)			0.006***	0.006***	0.006***	0.006***
			(6.017)	(6.221)	(6.240)	(6.493)
Interest Rate (%)			0.064***	0.059***	0.058***	0.060***
			(5.204)	(6.232)	(6.580)	(7.223)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	–
ZIP Code FE	–	–	–	–	–	Yes
# of Loans at Foreclosure	50,926	37,417	37,413	37,060	37,060	36,254
Adj. R-squared	0.615	0.622	0.867	0.871	0.873	0.891

Table 3: Mortgage-Level Analysis – The Changing Features of Mortgage Contracts in the Aftermath of Wildfires

*This table presents the cross-sectional estimation of interest rate (regressions (1) to (3)) and LTV (regressions (4) to (6)) at origination. Our variable of interest is an indicator which gets one if there is a wildfire in the last year in the ZIP code of the collateral property. Our control variables include the natural logarithm of loan balance, the natural logarithm of the FICO score of the borrower at origination, an indicator whether the interest rate is adjustable, the natural logarithm of the term to maturity, LTV (in regressions (1) to (3)), and the interest rate of the mortgage (in regression (4)). In regressions (2), (3), (5) and (6), we limit the sample to the loans that have an LTV less than 80% at origination. 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.*

	Interest Rate (%)			LTV (%)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Loans with LTV<80%		All	Loans with LTV<80%	
Wildfire Last Year (1=Yes)	0.054***	0.054***	0.056***	-3.486*	-3.118*	-5.969***
	(0.018)	(0.009)	(0.011)	(1.934)	(1.610)	(1.519)
ln(Loan Balance)	0.019	0.049	0.052	-0.463	0.115	6.156***
	(0.069)	(0.077)	(0.086)	(2.049)	(2.268)	(2.315)
ln(FICO)	-0.360	-0.308	-0.376*	39.055***	42.117**	25.958
	(0.220)	(0.243)	(0.225)	(14.800)	(18.562)	(20.063)
Adjustable (1=Yes)	-0.698***	-0.686***	-0.709***	0.465	-7.945	1.337
	(0.095)	(0.157)	(0.171)	(10.966)	(14.244)	(16.357)
ln(Term to Maturity)	0.943***	0.936***	0.951***	-0.418	2.846	4.060
	(0.211)	(0.222)	(0.220)	(4.853)	(2.767)	(2.954)
LTV (%)	0.001					
	(0.001)					
LTV<80% (1=Yes)	-0.114***					
	(0.026)					
Interest Rate (%)				7.729**		
				(3.582)		
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	–	Yes	Yes	–
ZIP Code FE	–	–	Yes	–	–	Yes
# of Loan Originations	12,625	8,932	8,596	12,625	8,932	8,596
Adj. R-squared	0.969	0.781	0.808	0.722	0.364	0.540

Table 4: 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

Table 5: Designing MBSs – The Benefits of Securitization: Returns at the ZIP and MBS Levels, Numerical Simulations

The table presents annualized average monthly returns, standard deviation of monthly returns, and sharp ration of monthly returns by quartiles of wildfire risk at ZIP code level and MBS level.

Level	10th Percentile	1st Quartile	Mean	Median	3rd Quartile	90th Percentile
Average Monthly Return (Annualized)						
ZIP Level	-0.18	0.85	10.05	1.45	2.26	3.39
MBS Level	0.51	3.16	4.22	5.03	5.71	5.77
S.D. Monthly Return (Annualized)						
ZIP Level	4.14	6.19	7.65	7.71	8.80	10.46
MBS Level	2.79	2.88	3.72	3.18	4.90	5.28
Sharpe Ratio of Monthly Returns						
ZIP Level	-2.70	-1.27	1.19	-0.41	1.07	3.80
MBS Level	-0.22	0.30	0.84	1.04	1.35	1.45

Table 6: MBS Pricing Analysis – Correlation of the National Wildfire Propensity Factor with the Term Structure of Interest Rates

This table presents the set of unconditional pairwise correlations between each of the wildfire propensity factors and the term structure of interest rates, measured by the (1) 1 Month T-bill yield (series DGS1MO), (2) the 5, 7-year yields (series DGS5 and DGS7), (3) the term premium measured as the difference between the yield on the 1-month T-bill and the 5, 7, 10, or 30 year Treasury yields (series DGS10 and DGS30). Definitions of the wildfire propensity scores presented in Section 2.2.

Wildfire Propensity	1 month	5y − 1 mo	7y − 1 mo	10y − 1 mo	30y − 1 mo	5y	7y
PS0	-0.14	-0.05	-0.06	-0.06	-0.05	-0.19	-0.21
p value	0.02	0.42	0.38	0.32	0.45	0.00	0.00
PS1	-0.01	-0.18	-0.19	-0.19	-0.17	-0.13	-0.16
p value	0.83	0.00	0.00	0.00	0.01	0.05	0.01
PS2	-0.01	-0.19	-0.19	-0.19	-0.17	-0.13	-0.16
p value	0.89	0.00	0.00	0.00	0.01	0.05	0.01
PS3	-0.01	-0.18	-0.19	-0.19	-0.17	-0.12	-0.16
p value	0.91	0.00	0.00	0.00	0.01	0.06	0.01

Table 7: MBS Pricing Analysis – Fama MacBeth Estimates of the Pricing of Wildfire Risk – log Price Level

These tables present the estimate $\hat{\gamma}$ of the impact of wildfire risk probabilities on the log price level of each tranche. This is the average of the cross-sectional coefficients for the wildfire beta β^w in the second-step regression at monthly frequency. Standard errors account for correlation structures described in Section 6.1. Such correlation structures allow for autocorrelation in $\hat{\lambda}_t$. The panel below provides estimates for different specifications using one of the five wildfire propensity scores, where PS0–PS3 refer to the four columns of Table 1. t-statistics are adjusted for Newey-West Autocorrelation in $\widehat{\gamma}_t$.

$\log p_{\tau dt}$, *log price of tranche τ of deal d in month t*

β of Cash Flows w.r.t. Wildfire Propensity Score 0				
Sample	Estimate	S.E.	t statistic	p value
All tranches	−0.330	0.275	−1.198	0.233
Tranche rank <0.5 (senior tranches)	−0.190	0.243	−0.784	0.435
Tranche rank >0.5 (junior tranches)	−0.283	0.236	−1.199	0.233
Most junior tranche	−0.484	0.176	−2.750	0.007
β of Cash Flows w.r.t. Wildfire Propensity Score 1				
Sample	Estimate	S.E.	t statistic	p value
All tranches	−1.631	0.487	−3.351	0.001
Tranche rank <0.5 (senior tranches)	−0.489	0.212	−2.302	0.023
Tranche rank >0.5 (junior tranches)	−1.436	0.473	−3.034	0.003
Most junior tranche	−0.845	0.215	−3.928	0.000
β of Cash Flows w.r.t. Wildfire Propensity Score 2				
Sample	Estimate	S.E.	t statistic	p value
All tranches	−1.594	0.508	−3.138	0.002
Tranche rank <0.5 (senior tranches)	−0.489	0.227	−2.151	0.033
Tranche rank >0.5 (junior tranches)	−1.421	0.491	−2.892	0.005
Most junior tranche	−0.881	0.198	−4.443	0.000
β of Cash Flows w.r.t. Wildfire Propensity Score 3				
Sample	Estimate	S.E.	t statistic	p value
All tranches	−1.160	0.374	−3.104	0.002
Tranche rank <0.5 (senior tranches)	−0.222	0.153	−1.445	0.151
Tranche rank >0.5 (junior tranches)	−0.955	0.347	−2.747	0.007
Most junior tranche	−0.621	0.125	−4.976	0.000

Table 8: MBS Pricing Analysis – Fama MacBeth Estimates of the Wildfire Risk Premium – Monthly log Price Changes

These tables present the estimate $\hat{\zeta}^w$ *of the impact of wildfire risk probabilities on returns (at the tranche-deal-month level). This is the average of the cross-sectional coefficients* $\hat{\zeta}_t^w$ *for the wildfire beta* β^w *in the second-step regression at monthly frequency when the dependent variable is the log price change. Standard errors account for correlation structures described in Section 6.1. Such correlation structures allow for autocorrelation in* $\hat{\lambda}_t$*. The panel below provides estimates for different specifications using one of the five wildfire propensity scores, where PS0–PS3 refer to the four columns of Table 1. t-statistics are adjusted for Newey-West Autocorrelation in* $\widehat{\gamma}_t$*.*

$\Delta \log p_{\tau dt}$*, log price appreciation of tranche* τ *of deal* d *in month* t

β of Cash Flows w.r.t. Wildfire Propensity Score 0				
Sample	Estimate	S.E.	t statistic	p value
All tranches	0.108	0.016	6.793	0.000
Tranche rank <0.5 (senior tranches)	0.165	0.031	5.395	0.000
Tranche rank >0.5 (junior tranches)	0.087	0.024	3.610	0.000
Most junior tranche	−0.004	0.016	−0.218	0.828
β of Cash Flows w.r.t. Wildfire Propensity Score 1				
Sample	Estimate	S.E.	t statistic	p value
All tranches	0.685	0.752	0.910	0.364
Tranche rank <0.5 (senior tranches)	0.281	0.135	2.079	0.040
Tranche rank >0.5 (junior tranches)	0.174	0.086	2.032	0.044
Most junior tranche	−0.031	0.038	−0.831	0.408
β of Cash Flows w.r.t. Wildfire Propensity Score 2				
Sample	Estimate	S.E.	t statistic	p value
All tranches	0.370	0.265	1.396	0.165
Tranche rank <0.5 (senior tranches)	0.273	0.131	2.091	0.039
Tranche rank >0.5 (junior tranches)	0.144	0.065	2.227	0.028
Most junior tranche	−0.036	0.037	−0.963	0.338
β of Cash Flows w.r.t. Wildfire Propensity Score 3				
Sample	Estimate	S.E.	t statistic	p value
All tranches	0.311	0.229	1.357	0.177
Tranche rank <0.5 (senior tranches)	0.206	0.102	2.024	0.045
Tranche rank >0.5 (junior tranches)	0.122	0.059	2.052	0.042
Most junior tranche	−0.022	0.028	−0.793	0.429

Table 9: MBS Pricing Analysis – Correlations of the National Wildfire Propensity Factor with 14 Factors

These two tables present a set of 5×14 unconditional correlations, between each of the 4 wildfire propensity scores built as in Section 2.2, and 14 factors: excess market return (mkt), size (smb), book-to-market (hml), profitability (rmw), and investment (cma) from Fama & French (2015), betting against beta (bab) in Frazzini & Pedersen (2014), gross profitability (gp) in Novy-Marx (2013), liquidity (psl) from Pástor & Stambaugh (2003), momentum (mom) in Carhart (1997), quality minus junk (qmj) in Asness et al. (2019), investment (ia) and profitability (roe) from Hou et al. (2015), coskewness (csk) from Harvey & Siddique (2000), and common idiosyncratic volatility (civ) from Herskovic et al. (2016). The factor longitudinal panel data set is from Harvey & Liu (2021). Each wildfire propensity score $PS0$ *to* $PS3$ *is a national score, the average across 5-digit ZIP codes of the wildfire propensity score at monthly frequency, weighted by the dollars of mortgage origination. The p value is computed for each correlation coefficient separately.*

Wildfire Propensity	Mkt-RF	SMB	HML	RMW	CMA	Mom12m	Coskewness
PS0	-0.06	-0.10	-0.05	0.06	-0.08	0.12	-0.01
p value	0.32	0.10	0.39	0.35	0.20	0.05	0.84
PS1	-0.02	-0.11	-0.06	0.06	-0.09	0.11	-0.04
p value	0.78	0.09	0.33	0.34	0.16	0.08	0.56
PS2	-0.02	-0.11	-0.06	0.06	-0.09	0.11	-0.04
p value	0.80	0.09	0.33	0.35	0.17	0.08	0.55
PS3	-0.02	-0.10	-0.06	0.06	-0.09	0.11	-0.04
p value	0.78	0.10	0.34	0.35	0.17	0.08	0.54

Wildfire Propensity	BetaLiquidityPS	R_ROE	R_IA	qmj	bab	GP	IdioVol3F
PS0	-0.07	0.14	-0.10	0.16	-0.03	0.09	0.07
p value	0.30	0.03	0.10	0.01	0.64	0.14	0.28
PS1	-0.10	0.12	-0.16	0.10	-0.06	0.08	0.04
p value	0.15	0.05	0.01	0.12	0.37	0.19	0.52
PS2	-0.09	0.12	-0.15	0.09	-0.06	0.08	0.04
p value	0.16	0.06	0.01	0.13	0.38	0.20	0.55
PS3	-0.09	0.12	-0.15	0.09	-0.05	0.08	0.04
p value	0.17	0.06	0.01	0.13	0.39	0.20	0.55

Table 10: Text Analysis of MBS Prospectuses

This table presents summary statistics of the analysis of the full text of MBS prospectuses. An observation is an MBS deal.

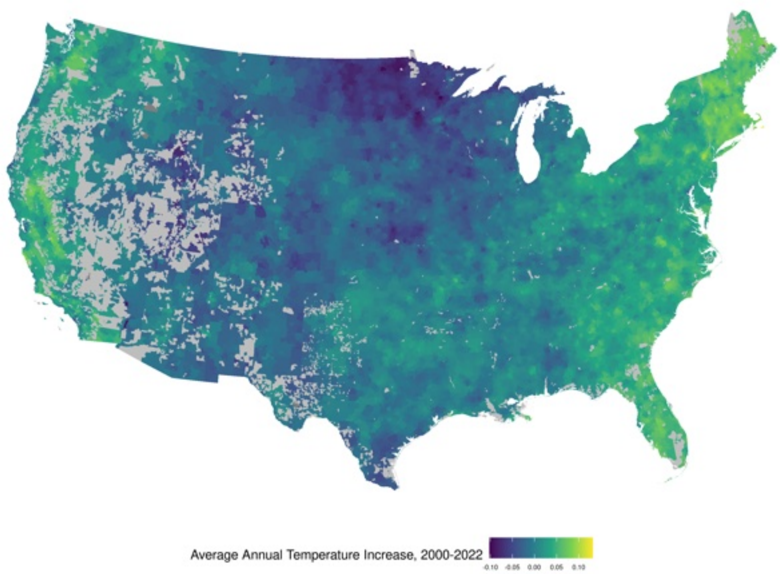
Variable	P10	P25	Average	S.D.	P75	P90	# of Deals
Wildfire, Wildfires							
Frequency per 100,000 words	0.00	0.00	0.61	0.97	1.05	2.21	482
Number of words per prospectus	0.00	0.00	1.02	1.60	2.00	4.00	482
Broader Set of Words							
Frequency per 100,000 words	8.36	11.46	14.79	5.41	18.61	21.62	482
Number of words per prospectus	11.00	16.00	23.58	10.02	30.00	36.00	482

Broader Set of Words: climate, warming, wildfire, hurricane, storm, flood, tornado, thunderstorm, typhoon, cyclone, heatwave, drought, rainstorm, blizzard", avalanche, mudslide, landslide, windstorm, hailstorm, ice, snowstorm, blaze, inferno, forest, campfire, conflagration, backfire, arson, flare-up.

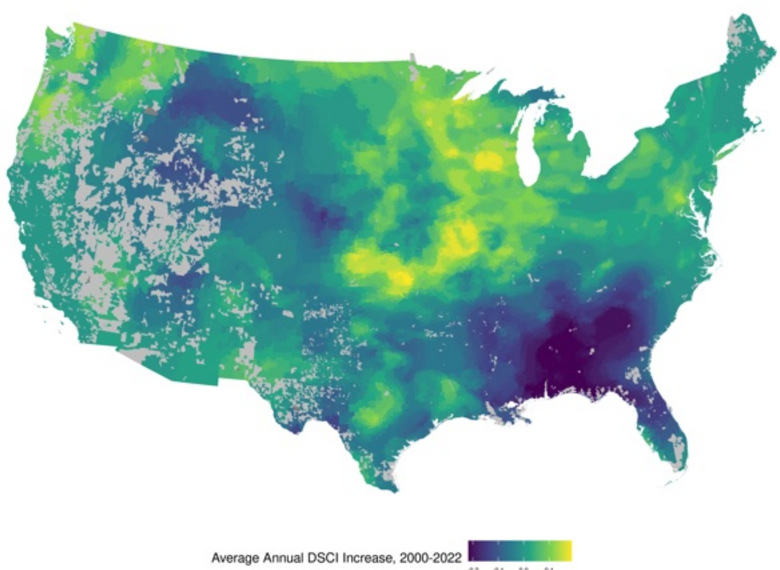
Appendix Figure A: Evolution of Temperatures (PRISM) and of the Drought Index – Average Annual Change

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)



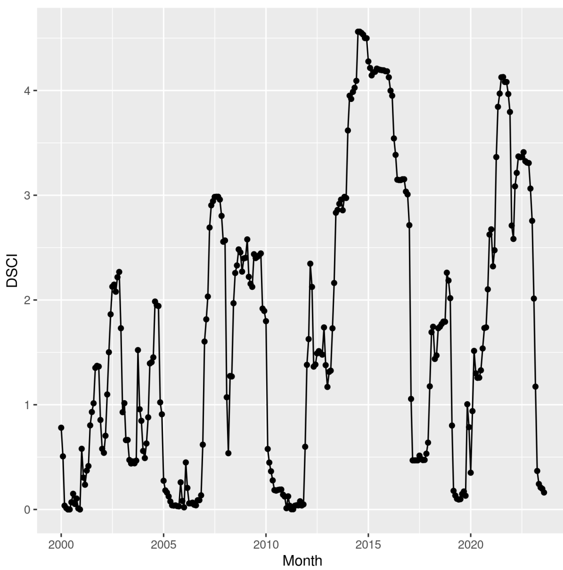
(b) 5-digit ZIP code Average Annual Change in the Drought Index, USDA DSCI (higher is drier).



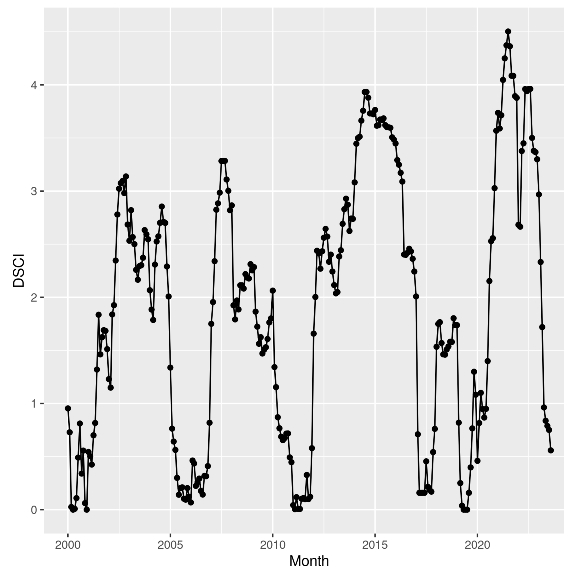
Appendix Figure B: Monthly Drought Index and Extreme Temperatures for two Wildfire-Prone States

The two charts of the upper panel present the average of the USDA DSCI drought index for two states: California and Nevada. Higher is drier. Data from the U.S. Drought Monitor hosted at the University of Nebraska-Lincoln. The two charts of the lower panel present the 90th percentile of temperatures for the same two states. Temperature data is from Oregon State University's PRISM project. Both the DSCI index and the temperature are averaged at the ZIP-code level, consistent with Specification 1.

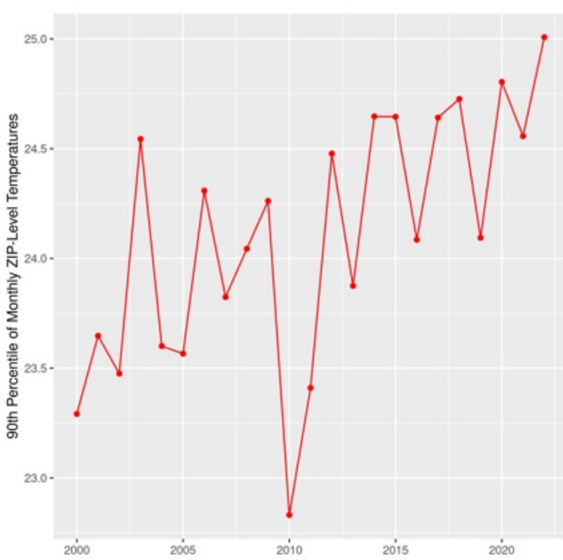
(a) California's Average Drought Index



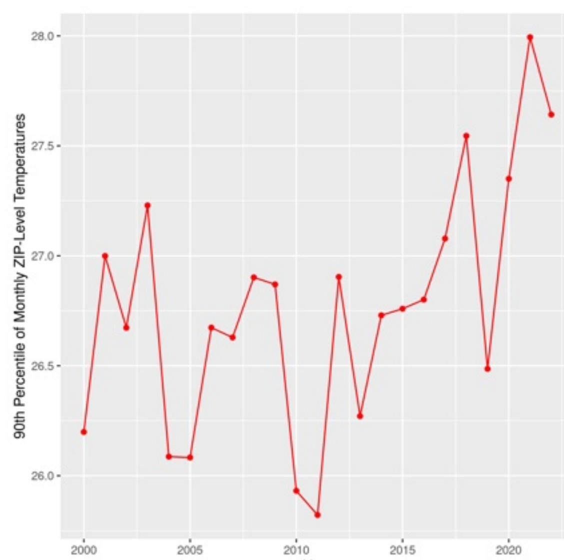
(b) Nevada's Average Drought Index



(c) California's 90th Percentile of Temperature



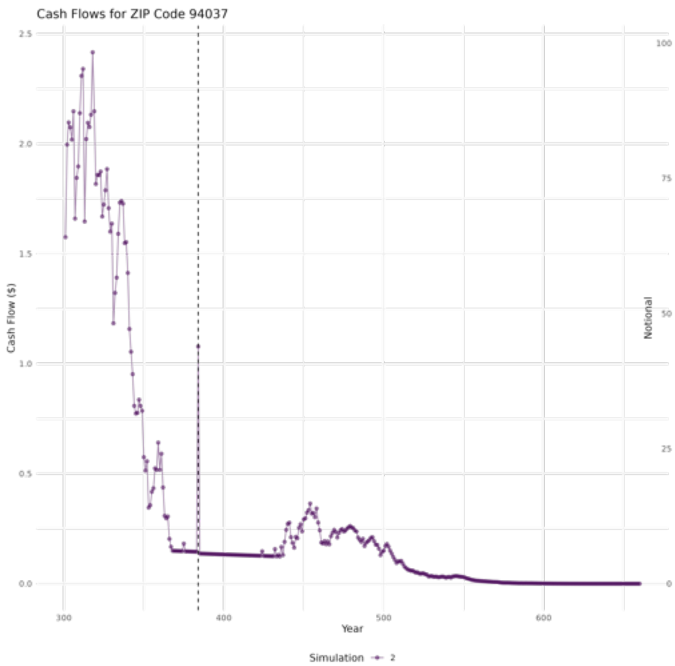
(d) Nevada's 90th Percentile of Temperature



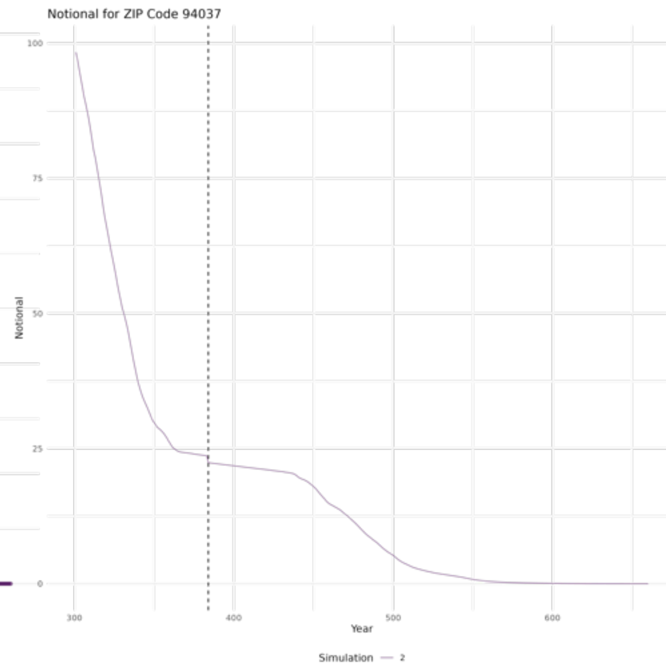
Appendix Figure C: Designing MBSs – Simulation Example, Cash Flow for One 5-Digit ZIP Code

This figure presents the path of cash flows, notional, prepayment rate, and remaining principal for one ZIP code in one interest rate simulation and one wildfire simulation. The vertical dotted line is for the wildfire. In total, we perform 50 interest rate and wildfire simulations per 5-digit ZIP code. These cash flow simulations are then weighted for each MBS. An MBS is a portfolio of mortgages across ZIP codes.

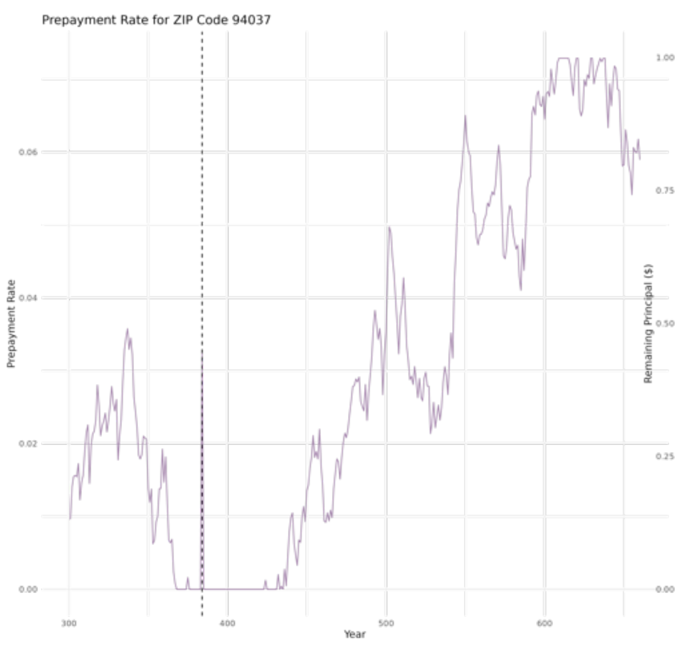
(a) Cash Flow $\mathrm{CF}_{j,t}$



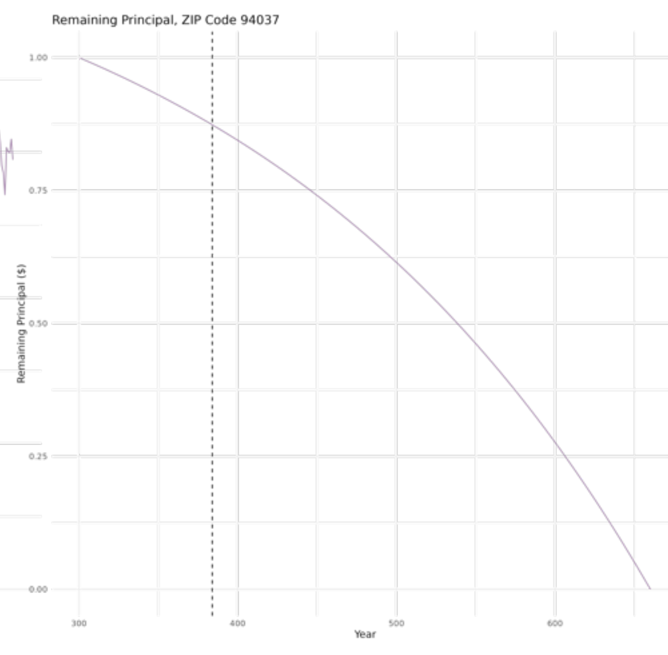
(b) Notional $N_{j,t}$



(c) Hazard Rate $\lambda_{j,t}$

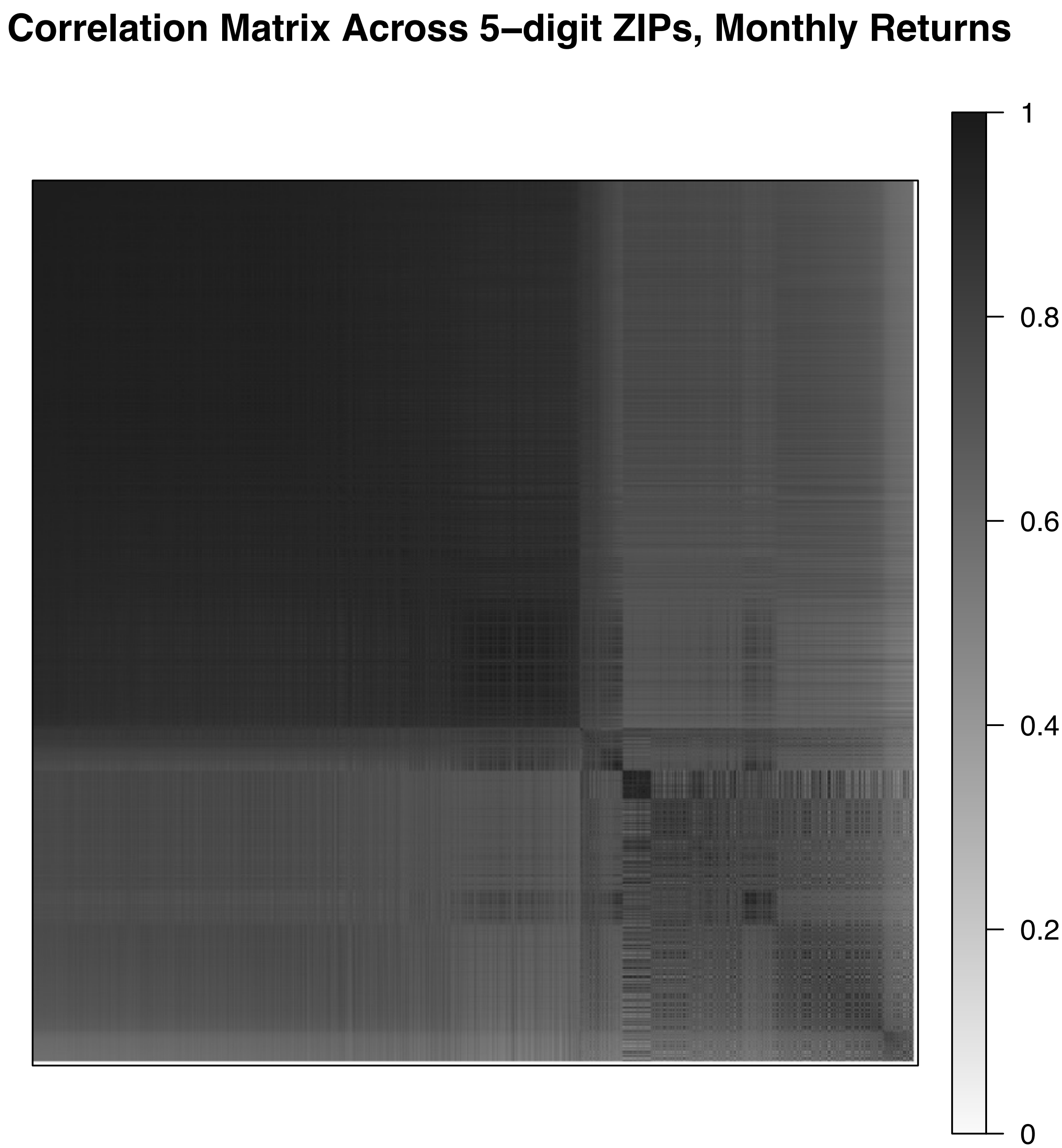


(d) Remaining Principal $I_{j,t}$



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 monthly returns of ZIP-level mortgage investments $Cor(\tilde{r}_{jt}, \tilde{r}_{j't})$ *for any pair of ZIP codes* j, j'. *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). The correlation matrix is ordered using the approach of Hahsler, Hornik & Buchta (2008). The number of rows and the number of columns are equal to the number of 5-digit ZIP codes of our sample, which includes the wildfire-prone states of California, Oregon, Washington, Indiana, Montana, Wyoming, Nevada, Utah, Colorado, Arizona, and New Mexico.*



Appendix Table A: Designing MBSs – Trade-Offs Between Wildfire Risk, Prepayment and Foreclosure Risk

This table presents the cross-sectional regressions of the baseline (1) prepayment and (2) foreclosure hazard rates, and the (3) mortgage interest rate at the ZIP level on each of the wildfire propensity score of the first column of Table 1. The baseline hazard rates are estimated using the logistic regression (16). The hazard rate and the interest rate are available in 5-digit ZIP codes with private label mortgage originations.

Panel A: Linear Regression on the Wildfire Propensity Score

	(1) Prepayment Hazard	(2) Foreclosure Hazard	(3) Interest Rate
(Intercept)	2.283***	0.174***	4.900***
	(0.044)	(0.012)	(0.013)
Wildfire Propensity Score	-0.023**	0.001	0.002
	(0.010)	(0.003)	(0.003)
Num.Obs.	2938	2938	2938

Panel B: Regression on 4 bins of the Wildfire Propensity Score

	(1) Prepayment Hazard	(2) Foreclosure Hazard	(3) Interest Rate
(Intercept)	2.229***	0.180***	4.895***
	(0.055)	(0.014)	(0.016)
Wildfire Propensity Score P60-P70	-0.138	-0.082**	-0.162***
	(0.145)	(0.038)	(0.042)
Wildfire Propensity Score P70-P80	0.106	-0.006	-0.016
	(0.145)	(0.038)	(0.042)
Wildfire Propensity Score P80-P90	0.490***	-0.005	0.115***
	(0.145)	(0.038)	(0.042)
Wildfire Propensity Score P90-P100	-0.157	0.037	0.129***
	(0.145)	(0.038)	(0.042)
Num.Obs.	2,938	2,938	2,938