Creative Destruction or Lasting Decline: Evidence from Post-Disaster Recovery

Yurou He* Ariel Ortiz-Bobea† Jiong Wu‡

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Abstract

Why do some local economies rebound from destructive shocks while others fall into persistent decline? We study how large-scale physical destruction reshapes spatial economic dynamics by developing a general equilibrium model of urban growth with housing and amenity externalities. The model predicts non-monotonic recovery patterns: low-productivity areas experience persistent losses, middle-productivity areas recover, and high-productivity areas undergo "creative destruction," realizing sustained gains. We test these predictions using parcel-level transaction and tax assessment data linked to more than 1,000 wildfires across the United States. On average, disasters reduce both land and building values in the long run, but the effects vary systematically with pre-disaster local productivity as predicted. Nearby unburned parcels exhibit similar post-disaster trajectories, indicating substantial spillover effects. The long-run effects of localized destruction depend critically on pre-disaster local productivity and spillovers.

Keywords: Natural disasters; Urban resilience; Property values; Spillovers; Wildfires
JEL Codes: Q54, R11, R52

1 Introduction

Why do some neighborhoods rebound after disasters while others stagnate or decline? Disasters that destroy surface buildings—fires, floods, and windstorms—have been shown to produce various recovery trajectories: some communities fail to recover, others return to prior trends, and still others surpass pre-disaster growth. How do pre-disaster local economic conditions—specifically, productivity—shape recovery paths a destroyed area will follow?

*Charles H. Dyson School of Applied Economics and Management, Cornell University. E-mail: yh878@cornell.edu.

†Charles H. Dyson School of Applied Economics and Management, Cornell University. E-mail: ao332@cornell.edu.

‡Department of Economics, Ohio State University. E-mail: wu.7224@osu.edu.

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And how do disasters act as catalysts that unlock rebuilding capacity and shift neighborhoods onto new growth trajectories? With climate change increasing the frequency and severity of natural disasters, these questions have become central to understanding urban resilience and long-run economic development.

To answer these questions, we build a general equilibrium model of urban growth in which landowners decide when, and with what quality, to replace durable buildings. The central mechanism is the housing and amenity externalities: the quality of neighborhood contributes to how an individual value their own property. Amenity provision is supported by local income which is directly linked to local productivity. Destruction does not have uniform consequences: in high-productivity regions, rebuilding occurs at higher quality, lifting both property and land values through stronger amenities and neighborhood spillovers. In low-productivity regions, however, rebuilding is constrained, leading to weaker recovery or even persistent decline. We derive a set of testable predictions to take to the data.

We use wildfires as natural experiments in our research design. Wildfires struck neighborhoods with diverse economic fundamentals across the United States thousands of times in the past decade. Conditional on regions where wildfires have occurred, the event is unpredictable in timing and location, providing a valuable natural experiment. Wildfires are destructive, damaging buildings and requiring substantial recovery expenditures. They hence open opportunities for large-scale reconstruction that rarely occur in regular cycles of urban renewal and potentially produce divergent recovery outcomes.

Our empirical analysis draws on a plot-level dataset from ATTOM, which provides tax assessments for all U.S. land parcels and properties from 2007 to 2022. We merge these records with wildfire burn-scar boundaries from the Monitoring Trends in Burn Severity (MTBS) project to obtain assessed land, building, and total values for plots inside burned areas and their surroundings. Validation with supplemental transaction data confirms that assessed values closely track sales prices, allowing us to measure changes in property values before and after disasters.

We estimate treatment and spillover effects of wildfires using a staggered difference-in-differences framework across locations with varying levels of local productivity. On average, wildfires have significantly negative long-run effects on property values in burned areas, yet these effects vary sharply with underlying local productivity, as proxied by pre-disaster land values. Ranking parcels by unit land value within each county, we show that low-productivity areas suffer steep declines and fail to recover fully after years, middle-productivity areas experience modest short-run losses followed by relatively quick recovery to pre-disaster level, and high-productivity areas not only avoid losses but instead experience sustained gains. Moreover, these heterogeneous effects extend beyond the fire's footprint: nearby unburned areas mirror the same positive or negative trajectory. Empirical results confirm the propositions of our theory.

Disasters compel landowners to rebuild simultaneously, and the collective quality of reconstruction determines neighborhood outcomes. When rebuilding upgrades the local building stock, spillovers raise surrounding land values and encourage further investment, creating self-reinforcing gains. When rebuilding replaces structures with lower-productivity ones, spillovers instead dampen values and slow recovery. Because individual landowners cannot normally coordinate to capture the diffuse benefits of their own reconstruction, such synchronized renewal rarely occurs under normal conditions. By removing older, low-value

structures and forcing widespread rebuilding, wildfires temporarily remove these coordination frictions—but whether the outcome is destructive or beneficial ultimately depends on landowners' expectations about the local environment.

A central challenge in empirically evaluating this mechanism is that housing quality is not directly observed. While changes in land and building values are consistent with upgrading or deterioration of the built environment, prices alone cannot distinguish between active reconstruction and passive revaluation. To address this gap, we complement our main results with direct evidence on rebuilding behavior. Using detailed assessor records, we examine whether key housing characteristics—such as construction year, interior layout, structural features, and amenities—change following wildfire exposure. By showing that disasters induce systematic and heterogeneous changes in these characteristics, we provide direct evidence that rebuilding activity and housing quality adjustment are central to post-disaster recovery dynamics.

The paper relates to a literature that studies how major shocks shape urban resilience, documenting a wide range of recovery trajectories. Some places experience persistent decline after disasters Ambrus et al. (2020); Dottori (2024); Hsiang and Jina (2014); Lynham et al. (2017); Meltzer et al. (2021); Ortega and Taspınar (2018), others return to pre-disaster trends Belasen and Polachek (2008, 2009); Cavallo et al. (2013); Davis and Weinstein (2002); Deryugina et al. (2018); Kocornik-Mina et al. (2020); Miguel and Roland (2011); Strobl (2011), and still others undergo "creative destruction," emerging stronger than before Hornbeck and Keniston (2017); Murphy and Strobl (2009); Siodla (2015); Zivin et al. (2023). Our study builds on these findings by using a unified setting—wildfires across the United States—to bring these divergent recovery paths together in a single empirical framework and examine the underlying sources of heterogeneity.

An important insight from the urban economics literature is that neighborhood spillovers play a central role in shaping these divergent recovery paths. Prior studies show that foreclosures, vacancies, and gentrification generate sizable externalities on nearby property values Campbell et al. (2011); Guerrieri et al. (2013); Diamond et al. (2019); Autor et al. (2014). Policy efforts such as urban renewal and slum clearance similarly sought to internalize these externalities by coordinating investments across neighborhoods, though with mixed success Ambrus et al. (2020); Collins and Shester (2013); Glaeser and Gyourko (2005); Hornbeck and Keniston (2017). We develop a theory of post-disaster rebuilding in which landowners make endogenous reconstruction and quality choices in the presence of local complementarities. The model shows that rebuilding incentives depend on pre-disaster local productivity, hence identical shocks can generate persistent divergence in housing quality.

Our study contributes to a growing literature that treats disasters as quasi-experiments to identify causal effects on local economies Davis and Weinstein (2002); Miguel and Roland (2011); Cavallo et al. (2013); Hornbeck and Keniston (2017). We extend this approach by leveraging property-level data that allow us to capture heterogeneous recovery dynamics within neighborhoods and across the value distribution Campbell et al. (2011); Diamond et al. (2019). In addition, we apply recent advances in staggered difference-in-differences estimation to address biases in dynamic treatment settings Sun and Abraham (2021); Wing et al. (2024); Callaway and Sant'Anna (2021). This combination of high-resolution data and modern methods enables us to provide new evidence on how disasters reshape urban trajectories through heterogeneous spillovers.

As rebuilding investment decisions generate large externalities, there is considerable scope for policy to coordinate recovery more effectively. While disasters can temporarily align rebuilding decisions and produce spillovers, such outcomes are not guaranteed and may even generate negative externalities in weaker local economies. Modern land-use regulations, zoning policies, and targeted subsidies can encourage investments that yield positive spillovers while discouraging rebuilding that entrenches inefficiencies. Neighborhoods also exhibit substantial heterogeneity in building quality, land use, and neighborhood conditions, suggesting that well-designed coordination policies could unlock productivity gains without the destructive costs of disasters. In this sense, recovery policy should aim to replicate the beneficial aspects of disaster-induced rebuilding—simultaneity and spillovers—while avoiding the economic and social losses associated with destruction.

2 Theoretical Framework

We extend the theoretical model of Hornbeck and Keniston (2017) to a general equilibrium framework and analyze landowners' decisions on when and with what quality to replace durable buildings. In doing so, we provide a micro-foundation for the hedonic rent function and derive analytical results on reconstruction responses to disasters. Crucially, our model shows that differences in local fundamentals generate heterogeneous recovery paths, as cross-building externalities determine whether destruction yields economic gains or losses. Finally, we derive a set of testable predictions to take to the data.

2.1 Environment

Agent preferences Consider a neighborhood with a unit measure of agents who live for infinitely many periods. Each agent derives intra-temporal utility from consuming a numeraire good and from one unit of housing:

$$u = c + H(q,\ Q,\ a),$$

where c is the quantity of the consumption good, and $H(q,\ Q,\ a)$ is the value of their housing. $H(q,\ Q,\ a)$ is strictly increasing in each of three arguments: the quality of the agent's own house q, the average quality of their neighboring houses Q, and the amenities of the surrounding area a. Agents cannot directly choose the quality of houses. $H(q,\ Q,\ a)$ is super-modular: $\frac{\partial^2 H}{\partial q \partial Q} > 0$ and $\frac{\partial^2 H}{\partial q \partial a} > 0$. The former reflects cross-plot externalities: higher neighborhood housing quality increases the value of one's own house. The latter captures that the valuation of housing quality is positively affected by its amenity. Agents may also migrate out of the neighborhood at no cost to receive an outside option value u_0. Time is discrete. The time discounter is β. Agents live hand-to-mouth.

Consumption good producer The production function of consumption good is:

$$y = AL,$$

where A is the labor productivity of consumption good and L the amount of labor employed. Producers operate in perfectly competitive markets for both the consumption good and labor.

Landlords Absentee landlords determine the quality of land parcels, q ($q \geq 0$). Landowners can choose to replace their outdated building of quality q with a new building of quality q' by paying the cost $c(q')$. We assume $c(0) = 0$, in other words, no fixed replacement cost. Buildings are occasionally destroyed by disasters with probability d. When destroyed, the parcel quality is reset to 0.

Government The government finances local amenities by taxing agents' income at rate τ. The total tax revenue is T, which is used to provide amenities according to the production function $a(T)$, where $a(T)$ is nonnegative and strictly increasing in T.

2.2 Equilibrium

Freely mobile agents maximize their utility given the housing they occupy. This yields the following rent function:

$$r = (1-\tau)w - u_0 + H(q,\ Q,\ a), \tag{1}$$

where w is the wage received. The outside option value u_0 pins down the indirect utility level of agents. After paying rent, agents spend all remaining income on consumption goods.

Profit-maximizing producers determine the equilibrium wage through the first-order condition:

$$w = A. \tag{2}$$

Local productivity is thus directly linked to household income. Non-profit government balances the budget of amenity provisions with tax revenues. Hence, we can rewrite the rent as a function of own housing quality, neighborhood housing quality, and local productivity:

$$r(q,\ Q,\ A) = (1-\tau)A - u_0 + H(q,\ Q,\ a(\tau A)). \tag{3}$$

This rent function is essentially hedonic.

Given the rents they can collect from agents, landlords maximize the net present value of their parcels. Their optimization problem is represented by the Bellman equation:

$$V(q,\ Q,\ A) = \max \begin{cases} r(q,\ Q,\ A) + \beta\left(dV(0,\ Q',\ A) + (1-d)V(q,\ Q',\ A)\right), \\ r(q^*,\ Q,\ A) + \beta\left(dV(0,\ Q',\ A) + (1-d)V(q^*,\ Q',\ A)\right) - c(q^*). \end{cases} \tag{4}$$

where Q' is the average neighborhood quality in the next period, and $q^* = \arg max_q\, r(q,\ Q,\ A) + \beta\left(dV(0,\ Q',\ A) + (1-d)V(q,\ Q',\ A)\right) - c(q)$. To illustrate, a landlord who has a property with quality q decides whether to keep the same quality this period or replace it with a quality q^* and pay the cost $c(q^*)$. If the property is destroyed by a disaster, quality falls to zero, and the parcel yields land value $V(0,\ Q,\ A)$. We define the building value as the difference between positive-quality and zero-quality land values: $V(q,\ Q,\ A) - V(0,\ Q,\ A)$.

We focus on the steady state equilibrium, in which the distribution of q is stationary and the average neighborhood quality Q remains constant. The equilibrium consists of a distribution of q such that (4) is satisfied for each q.[1]

[1]The quality cost is in units of consumption goods. So is amenity production input. Landlords consume their intra-temporal income: $r - c\mathbf{1}\{replacement\}$. The market clearing condition of consumption goods is satisfied.

2.3 Model Predictions

There are two key endogenously determined quality levels for landlords, implied by (4). The first is the optimal replacement quality q^*, which is the quality a landlord would choose when replacing a building. Given the neighborhood average housing quality Q and regional productivity A, we can pin down q^* by (4). The second is the replacement threshold $\underline{q}$. If the quality of a property falls below $\underline{q}$, landlords are better-off replacing it with q^*. The monotonicity of Bellman equation ensures the existence of such a threshold:

$$V(\underline{q},\ Q,\ A) = V(q^*,\ Q,\ A).$$

When a property is destroyed by a disaster and its quality collapses to zero, the landlord will rebuild at q^* since there is no fixed cost, $c(0) = 0$. In the absence of destruction, if the housing quality remains above $\underline{q}$, it will remain unchanged throughout the period. Therefore, there could be multiple equilibria set of q, which are all above $\underline{q}$.

Lemma 1. *The replacement threshold $\underline{q}$ is strictly smaller than optimal new quality q^*. Moreover, both $\frac{dq^*}{dA}$ and $\frac{dq^*}{dQ}$ are positive.*

Lemma 1 summarizes the relationship between $\underline{q}$ and q^*. Intuitively, higher productivity raises tax revenues through higher incomes, enabling the government to provide better local amenities. Higher amenity levels increase the marginal value of housing quality, giving landlords stronger incentives to rebuild at higher quality. Neighborhood quality reinforces this mechanism through housing externalities: as surrounding properties improve, the value of upgrading one's own property rises, further encouraging investment.

The gap between $\underline{q}$ and q^* is crucial for understanding how disasters affect the average rebuilt housing quality in the destroyed areas. If the majority of destroyed houses have pre-disaster quality above q^*, then after destruction they will be rebuilt at q^*, which is lower than their original quality. This lowers average housing quality in the razed neighborhood area, thereby reducing the land and building values. On the contrary, if the majority of houses destroyed have pre-disaster quality below q^*, the rebuilding process raises their quality. However, if the replacement threshold $\underline{q}$ is higher than q^*, there will not be any houses that can experience quality improvement after disasters. To rationalize the existence of properties with quality lower than q^*, one may think of them as houses that have depreciated over time to low quality level.

Housing externalities will further affect local land value and generate spillover effects to the properties that are not directly affected by disasters. If many razed properties are rebuilt to have higher qualities than before, the average neighborhood quality will rise. As agents also value their neighborhood, land value will be higher. For those unaffected properties, their building values, $V(q,\ Q',\ A) - V(0,\ Q',\ A)$, are higher due to higher average neighborhood quality. The main intuition is that as people value their neighborhood environment, collective reconstruction can raise their valuation for the land in that area, hence their buildings.

To formalize this mechanism, we define a set of houses destroyed by a disaster as $\{q\}_D$, assumed to be uniformly distributed from $\underline{q}$ to some upper bound $\bar{q}_D$. A more general characterization of destruction effects is summarized by lemma 2 below:

Lemma 2. *Let the average quality of destroyed properties be Q_D. If $Q_D < (>) q^*$, $q^{*,post} > (<) q^*$. Moreover, $V(0,\ Q^{post},\ A) > (<) V(0,\ Q,\ A)$.*

Regional productivity determines the optimal replacement quality and is therefore central to explaining heterogeneous recovery after disaster shocks. As shown in Lemma 1, given a set of property quality q, higher productivity raises the optimal replacement quality q^*. When a fraction of properties get destroyed, higher-productivity regions are more likely to rebuild at higher quality, and vice versa. The following proposition establishes the heterogeneous effects of disaster shocks:

Proposition 1. *Given the average quality of destroyed properties, Q_D, there exists a productivity threshold $\bar{A}$ such that average building values and land prices fall after a shock if $A < \bar{A}$ and rise if $A \geq \bar{A}$. The threshold $\bar{A}$ is pinned down by:*

$Q_D = \arg\max_q \; r(q,\ Q,\ \bar{A}) + \beta \left(dV(0,\ Q,\ \bar{A}) + (1-d)V(q,\ Q,\ \bar{A}) \right) - c(q).$

Intuitively, for a given level of direct disaster impact Q_D, a sufficiently productive region can recover and even improve average housing quality, while a low-productivity region suffers long-run declines. Higher productivity enhances local amenity provision, which raises the marginal value of housing quality. In such environments, landlords can charge higher rents and are more willing to invest in better-quality rebuilding. This channel explains why building values recover more strongly in productive communities. Even undeveloped land can appreciate in value if neighborhood quality improves through cross-plot externalities.

The model clarifies how disaster shocks interact with local productivity to shape long-run recovery outcomes. Landlords' rebuilding decisions hinge on the optimal replacement quality, which increases with both neighborhood quality and regional productivity. This mechanism implies that destruction does not have uniform consequences: in high-productivity regions, rebuilding occurs at higher quality, lifting both property and land values through stronger amenities and neighborhood spillovers. In low-productivity regions, however, rebuilding is constrained, leading to weaker recovery or even persistent decline. Proposition 1 formalizes this heterogeneity, showing that recovery depends on whether regional productivity surpasses a threshold level, such that the average rebuilt quality exceeds the average pre-disaster quality. These results motivate the following testable empirical predictions:

Testable empirical predictions Properties located in higher-productivity neighborhoods should not only recover more fully after a wildfire but may even surpass their pre-disaster values, while properties in less productive neighborhoods should experience sustained losses. Pre-fire property values serve as a proxy for local productivity and thus provide a natural way to test these predictions. From the model above, one can also tell that high productivity contributes to high property values and land values. Moreover, there will be corresponding spillover effects to the neighboring unburned buildings.

By tracing property-level trajectories across the value distribution, the empirical analysis examines whether disasters amplify existing heterogeneity: reinforcing advantages in productive neighborhoods and entrenching disadvantages in less productive ones.

3 Background and Data

We now turn to the empirical analysis to test these predictions. Specifically, we examine wildfires as a natural experiment, linking detailed burn perimeters to parcel-level tax

assessment data. This setting allows us to evaluate whether the heterogeneous recovery patterns—persistent decline, return to baseline, or creative destruction—emerge in practice across different local contexts.

3.1 Why Wildfires?

The questions examined in this paper apply broadly to disasters that simultaneously destroy large portions of the built environment. A substantial body of research has analyzed post-disaster recovery in the aftermath of earthquakes Davis and Weinstein (2002); Hornbeck and Keniston (2017); Miguel and Roland (2011), floods Deryugina et al. (2018), hurricanes Belasen and Polachek (2008, 2009); Deryugina (2017); Deryugina et al. (2018), fires Siodla (2015); Hornbeck and Keniston (2017), and even wars Brakman et al. (2004); Davis and Weinstein (2002). These events—whether natural disasters or man-made accidental destruction—share the common feature of compelling widespread and simultaneous rebuilding, thereby providing a natural setting to study how major shocks reshape urban trajectories.

Here we focus on wildfires as our case of interest for three main reasons. First, they occur frequently: the United States experiences an average of roughly 70,000 wildfires each year. Even when restricting attention to events that destroyed at least 30 properties, our 15-year sample still includes more than one thousand wildfires, providing substantial variation for analysis. Second, wildfires are geographically widespread, affecting communities across nearly all regions of the United States (Figure S7). Third, the MTBS project provides detailed burn perimeters that can be precisely matched to parcel-level tax assessment records. This precision enables us to estimate both the direct effects of wildfires on burned parcels and the spillover effects on nearby unburned parcels. To our knowledge, this is the first study to combine MTBS wildfire boundaries with nationwide parcel-level tax assessments to analyze post-disaster urban recovery at scale, which represents a central contribution of our work.

Last but not least, wildfires are becoming increasingly important in the context of climate change, and a growing body of research focuses specifically on their economic consequences Bayham et al. (2022); Kochi et al. (2010); Westerling et al. (2006). Our study contributes to this literature by providing new evidence on the medium- to long-run impacts of wildfires on regional economies across the United States.

3.2 Data

Our primary dataset is parcel-level tax assessments from ATTOM, compiled from county assessor offices and covering the universe of U.S. parcels between 2007 and 2022. These records report the centroid location of each parcel, assessed market values for land and buildings, and key characteristics such as parcel area and property type. Because most jurisdictions report assessments annually, the data allow us to construct a panel of property values over time.

A natural concern is whether assessed market values provide a valid proxy that accurately reflects underlying economic conditions. To validate this, we use another parcel-level dataset from ATTOM: transaction records compiled from county recorder offices that cover

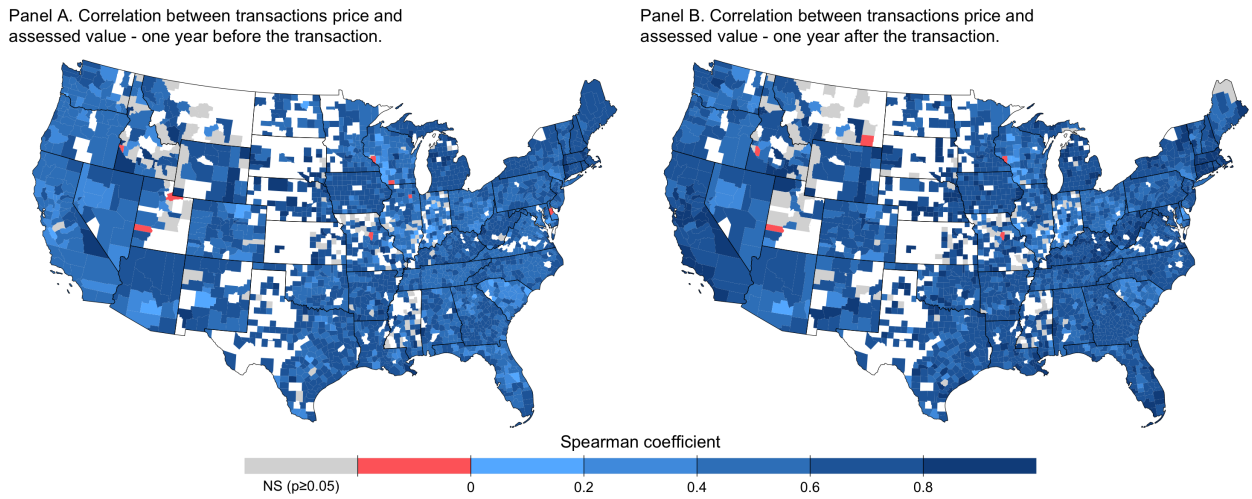


Figure 1: Correlation Between Transaction Prices and Assessed Values at the County Level

Note: Panel A maps the county-level correlation between property transaction prices and assessed values one year prior to the transaction. Panel B maps the same correlation one year after the transaction. Darker blue shading indicates stronger positive correlations (higher Spearman coefficients), while red shading indicates negative correlations. Counties shaded in gray represent statistically insignificant correlations at the 5% level. Together, the two panels demonstrate that assessed values track transaction prices closely across most counties, with generally stronger and more consistent correlations observed after the transaction year.

the universe of U.S. parcels from 2007 to 2022. These records report the timing and price of each land and property transaction, allowing us to compare assessed market values with actual transaction prices for parcels that change hands during our sample window. Specifically, we compare transaction prices with assessed values recorded immediately before and after the transaction. This approach reflects institutional practices: while counties do not always reassess properties annually, they almost always update assessed values following a transaction. California represents an extreme case, where assessed values are only updated upon sale. We therefore expect the market values assessed after a transaction to align most closely with observed market prices, while those assessed before the transaction align least. Together, these two correlations provide a lower and upper bound on the accuracy of assessed values as a proxy for market prices. Figure 1 plots the Spearman correlation between assessed values and transaction prices. Panel A maps county-level correlations using assessed values recorded one year before transactions, while Panel B reports the corresponding correlations one year after. In most counties, the correlation is strongly positive and statistically significant, with a clear strengthening after transactions. This pattern indicates that assessed values closely track market prices, validating their use as a consistent proxy for property value dynamics in our analysis.

On the wildfire side, we use data from the Monitoring Trends in Burn Severity (MTBS) project, which has documented large wildfires across the United States since the mid-1980s. MTBS provides detailed geospatial information on burn perimeters, allowing us to precisely identify parcels directly affected by fire as well as those located just outside the burn scar. This spatial precision enables us to disentangle the direct impacts of wildfires from spillover effects on nearby unburned parcels.

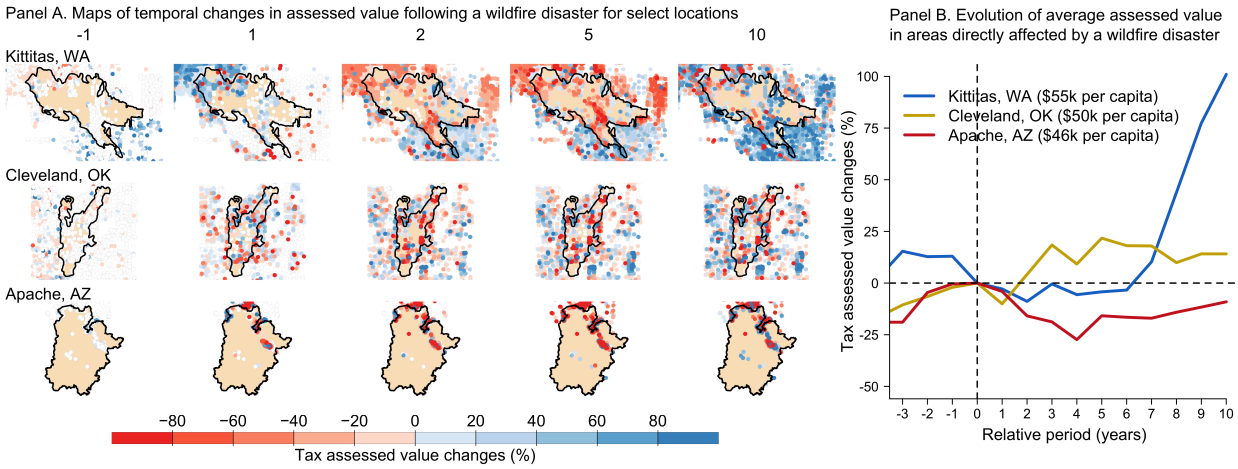


Figure 2: Temporal Evolution of Assessed Property Values Following Wildfires in Selected Locations

Note: Panel A shows the spatial distribution of changes in tax assessed property values before and after wildfires for three representative counties: Kittitas, WA; Cleveland, OK; and Apache, AZ. Each column corresponds to a different relative year since the wildfire event (−1, 1, 2, 5, and 10), with colors indicating percentage changes in assessed value. Panel B presents the average evolution of assessed values in directly affected areas for the same locations. The blue line corresponds to Kittitas, WA (with a per capita value of $55,000), the yellow line to Cleveland, OK ($50,000), and the red line to Apache, AZ ($46,000). The vertical dashed line marks the wildfire year, and the horizontal dashed line indicates no change in assessed value. Together, the panels illustrate the heterogeneity in post-wildfire recovery trajectories across regions with different baseline property values.

We then combined these two datasets for our analysis. Treatment and spillover areas are defined using MTBS boundaries: parcels within the burn perimeter are classified as treated, while those outside but within 100 meters of the boundary are classified as spillover. To visualize the breadth of the data, Figure [fig:motivation] presents divergent recovery trajectories after wildfires in three representative counties. Panel A maps the spatial evolution of property values before and after the fires, while Panel B plots average assessed value trajectories over time. The contrasts are sharp: in high-value Kittitas, housing values recover quickly and even surpass pre-disaster levels; in mid-value Cleveland, values rebound modestly; and in low-value Apache, values decline persistently. Together, the figure highlights the empirical heterogeneity that motivates our analysis—similar shocks can generate stagnation, recovery, or creative destruction depending on local fundamentals.

To capture heterogeneity in local productivity, we construct a measure of pre-disaster property rankings. For each parcel, we calculate a unit parcel value by dividing the total assessed market value by the parcel area. Parcels are then ranked within each county by this unit parcel value and assigned to value-based quintile groups.

4 Empirical Strategy

To estimate the causal effects of wildfires on land and building values, we begin by defining a sample of treated and control parcels that yields credible counterfactual comparisons. A key

identification concern is that wildfire-prone locations differ systematically from places that never experience wildfires. For example, dense urban cores are typically less exposed than communities located near wildland–urban interfaces. To address this concern, we restrict the sample to parcels located within wildfire perimeters or in nearby surrounding areas that experience at least one wildfire during the study period. Identification therefore comes primarily from within–at-risk comparisons across cohorts and over time, using not-yet-treated parcels as clean controls. In addition, we exploit comparisons with a localized never-treated group—parcels that are never burned but are located in close proximity to treated areas and thus face similar underlying wildfire risk. Together, these restrictions ensure that treated parcels are compared to economically and environmentally comparable controls, minimizing confounding from systematic differences between wildfire-prone and non–wildfire-prone locations.

Wildfire exposure occurs at different times across locations, generating a staggered treatment setting. We therefore estimate average and dynamic treatment effects using a stacked difference-in-differences (stacked DiD) design, following Wing, Freedman, and Hollingsworth (2024). This approach is particularly well suited to our context because wildfire exposure has become increasingly uneven over time: both the frequency of fires and the total area burned have risen sharply in recent decades, largely driven by rising fuel aridity and climate change (Burke et al. 2021). As a result, conventional event-study aggregations are sensitive to compositional changes across event time.

To address this concern, we adopt a stacked DiD approach that constructs and stacks cohort-specific sub-experiments and restricts attention to a balanced event window in which the same set of wildfire cohorts contributes to identification at each event time. A balanced event window is a trimmed set of sub-experiments that is balanced over a fixed event time window. This design ensures that differences across event time reflect dynamic treatment effects and pre-trend diagnostics, rather than changes in the composition of treated cohorts driven by the rapidly changing wildfire risk environment.

4.1 Dynamic Effect (Event-Study)

To study the timing and persistence of wildfire impacts, we estimate a dynamic event-study specification within a stacked DiD design. Specifically, we estimate the following equation on the stacked sample of cohort-specific sub-experiments:

$$y_{ict} = \alpha_i + \lambda_{ct} + \sum_{k \neq 0} \beta_k \, \mathbf{1}\{t - T_i = k\} \, \mathbf{1}\{D_i = 1\} + X_{it}'\gamma + \varepsilon_{ict}, \tag{5}$$

where y_{ict} is the log assessed land or building value of parcel i in county c and year t. The indicator $D_i = 1$ denotes parcels exposed to a given wildfire event. T_i is the first year of exposure. Event time k indexes years relative to the wildfire, with $k = 0$ omitted as the reference period. The coefficients $\{\beta_k\}$ trace the evolution of property values before and after wildfire exposure. Because the stacked design restricts attention to a balanced event window and holds the composition of treated cohorts fixed across event time, the pre-exposure coefficients provide a valid diagnostic for cohort-specific parallel trends, while the post-exposure coefficients capture the dynamic response of property values to wildfire exposure. Parcel fixed effects α_i absorb time-invariant heterogeneity at the parcel level, while

county-by-year fixed effects λ_{ct} control for local economic and policy shocks common to all parcels within a county-year. The standard errors are two-way clustered at the disaster and year level.

Consistent with the stacked DiD design, we apply a common trimming rule across all specifications to ensure that treated cohorts at the beginning and end of the sample have sufficient comparison units. Specifically, we require each treated cohort to have at least five pre-treatment years [2] and eight post-treatment years [3] of observations. As a result, with the data spaning 2007–2022, the effective treatment window spans 2012–2014, yielding three wildfire cohorts. Event-study estimates are therefore reported over a window covering five years before and eight years after wildfire exposure.

We estimate equation (5) separately for two samples. For the direct treatment effect, we define treated parcels as those located within the wildfire perimeter. For the spillover effect, treated parcels are those located outside but within 100 meters of the perimeter. In each case, the control group consists of (i) not-yet-treated parcels that will be exposed in a future wildfire but are untreated during the event window of the current cohort, and (ii) a localized never-treated group of parcels located in a 500–1000 meter ring around the wildfire perimeter that are never burned during the study period. These parcels face similar underlying wildfire risk and local conditions but are not directly exposed, making them appropriate controls within each cohort-specific comparison.

Consistent with the stacked DiD framework, equation (5) is estimated on the stacked sample using cohort-specific weights so that treated and control observations contribute symmetrically across sub-experiments. Under a cohort-specific parallel trends assumption conditional on the fixed effects, this approach identifies a trimmed aggregate average treatment effect on the treated (ATT) at each event time.

4.2 Average Post-Disaster Effects

To summarize the overall impact of wildfire exposure, we report an average post-disaster treatment effect constructed from the dynamic event-study estimates. We aggregate the post-exposure coefficients from the stacked event-study specification described in Section 4.1. This approach ensures that the average effect is identified from the same balanced sample of cohorts and relies on the same identifying assumptions as the dynamic analysis.

Formally, let $\{\beta_k\}$ denote the event-time coefficients from equation (5), where k indexes years relative to first wildfire exposure and $k = 0$ is the omitted reference period. We define

[2] The five-year pre-treatment window is used to assess pre-trends. Because our data begin in 2007 (one year prior to the Global Financial Crisis), we are concerned that the early years of the sample may not be fully representative of normal market conditions. By including these early years exclusively in the pre-treatment period, they do not directly affect the estimation of post-treatment effects. As a robustness check, Figures S4-S6 in the appendix reports results that drop the first three sample years and begin the analysis in 2010, leaving only two pre-treatment years; the qualitative patterns and magnitudes of the estimates remain similar.

[3] The choice of a relatively long post-disaster horizon is motivated by our study objective: understanding medium- to long-run recovery dynamics following wildfires. Existing evidence suggests that household and housing recovery after major disasters often takes several years. A shorter post-treatment window would therefore be insufficient to characterize longer-run effects. We adopt an eight-year post-treatment window as our baseline to allow sufficient time for recovery to unfold.

the average post-disaster effect as the equally weighted mean of the post-exposure coefficients over a fixed event window $\mathcal{K} = \{1, 2, 3..., K\}$:

$$ATT^{post} = \frac{1}{\mathcal{K}} \sum_{k \in \mathcal{K}} \beta_k, \tag{6}$$

Inference for the aggregated effect is conducted via a linear hypothesis (Wald) test on the post-exposure event-time coefficients, using the variance–covariance matrix from the stacked event-study regression. Standard errors therefore inherit the two-way clustering by disaster and year used in the dynamic specification. Specifically, we test whether the average of the post-disaster coefficients differs from zero.

This estimand captures the average change in property values following wildfire exposure over the specified post-event horizon. By construction, it corresponds to a trimmed aggregate average treatment effect on the treated (ATT) for the cohorts included in the stacked sample. As in the dynamic analysis, we estimate the average post-disaster effect separately for parcels directly exposed to wildfire and for parcels subject to spillover exposure.

4.3 Overall Effects and Heterogeneity

We first estimate the stacked DiD specifications described in Sections 4.1 and 4.2 on the full sample to characterize the overall average effect of wildfire exposure. Specifically, we construct cohort-specific sub-experiments, restrict attention to a balanced event window, and estimate dynamic and average post-disaster effects using not-yet-treated and localized never-treated parcels as controls. These estimates summarize the average post-disaster dynamics and aggregate treatment effects across all parcels in the at-risk sample, providing a benchmark against which distributional differences in recovery can be evaluated.

To examine heterogeneity in recovery trajectories, we then stratify parcels by their pre-disaster unit parcel value and rank them within each state. Parcels are grouped into quintiles based on this ranking, which we interpret as proxies for differences in local economic productivity and baseline neighborhood conditions. Rather than interacting quintile indicators with the treatment variable in a single regression, we estimate the stacked DiD specifications described in Sections 4.1 and 4.2 separately for each quintile group. Within each quintile subsample, we implement the same stacked event-study and aggregation procedures as in the baseline analysis. This approach provides a flexible, nonparametric characterization of distributional differences in post-disaster recovery dynamics.

5 Results

Our theory in Section 2 predicts that these divergent price dynamics arise because rebuilding incentives differ across locations with different pre-disaster local productivity, leading to systematic differences in post-disaster housing quality.

5.1 Treatment Effect

We begin by examining the direct effects of wildfires on parcels located inside the burn perimeter. Because these parcels experience physical destruction, we expect an immediate decline in building values, while changes in land values reflect longer-run adjustments driven by reconstruction quality, neighborhood spillovers, and local economic fundamentals. We first present results for the full sample and then examine heterogeneity by pre-disaster parcel rank. Consistent with the theoretical framework, post-disaster outcomes may take the form of recovery or continued deterioration, depending on local productivity and incentives to rebuild.

Before decomposing these effects into land and building components, we first study impacts on total tax-assessed market value. In the assessment data, three value measures are reported for each parcel—land value, building value, and total value—where total value is defined as the sum of land and building assessments. While most parcels report all three components, a nontrivial share of observations include only the total assessed value without a separate breakdown. As a result, analyses based on total value retain the largest and most comprehensive sample. We therefore begin by presenting stacked event-study estimates of wildfire effects on total assessed market values, both for the full sample and by pre-disaster unit parcel value quintiles, before turning to the land and building components to examine differential adjustment mechanisms.

Total values

Figure 3 reports stacked event-study estimates of the treatment effects of wildfires on the log of total tax-assessed market value (land + building), estimated for the full sample and separately by quintiles of pre-disaster unit parcel value (ranked within state). Panel A presents the full-sample profile. The pre-event coefficients are close to zero and do not display systematic movements leading up to the wildfire, providing little evidence of differential pre-trends. Following exposure, total assessed values decline and remain negative throughout most of the post-event window. After an initial drop in the first few post-event years, estimates settle into a persistently negative range, as reflected by the horizontal red line summarizing the average post-disaster effect.

Panels B–F report the same event-study specification estimated separately for the first through fifth quintiles of the pre-disaster unit value distribution. The first three quintiles (Panels B–D) exhibit broadly similar dynamics: total values fall after wildfire exposure and remain persistently below baseline. In contrast, the upper part of the distribution displays markedly different patterns. In the fourth quintile (Panel E), post-event coefficients are negative but smaller in magnitude and generally statistically indistinguishable from zero, indicating more limited average losses in total assessed value. The fifth quintile (Panel F) is distinct: post-event estimates are close to zero in the short run and become positive in later years, with point estimates on the order of five percent, suggesting that the highest-value parcels do not experience sustained total-value losses and instead exhibit net increases over the post-disaster horizon.

Taken together, the figure reveals pronounced heterogeneity in overall property-value responses to wildfire exposure across the pre-disaster value distribution. Lower-value parcels

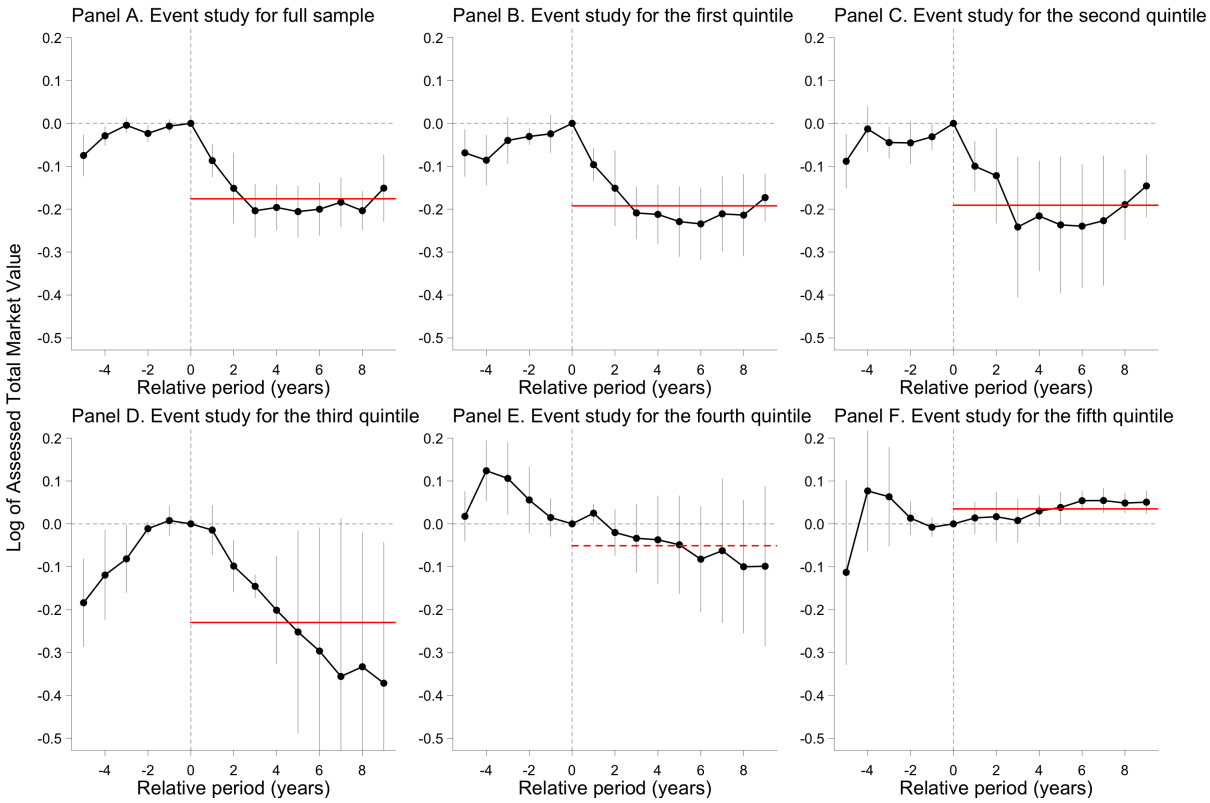


Figure 3: Treatment Effects of Wildfires on Total Assessed Values

Note: This figure presents estimates of wildfire treatment effects on total tax-assessed market values for parcels located within the burn perimeter, shown for the full sample and separately by pre-disaster unit parcel value quintiles (Proxy for Local Productivity). Panel A shows the event-study dynamic estimates for the full sample. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

experience large and persistent declines in total assessed values following wildfire events. In contrast, higher-value parcels exhibit markedly different dynamics: rather than suffering losses, total assessed values rise above pre-disaster levels in the post-event period. This pattern is consistent with a form of spatially uneven creative destruction, in which wildfire exposure accelerates upgrading and reinvestment in the highest-productivity locations while amplifying losses in lower-value areas.

Building values

Figure 4 reports stacked event-study estimates of the effects of wildfires on the log of tax-assessed building market values, for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A presents the full-sample profile. The pre-event coefficients are small and close to zero, with no pronounced movements prior to exposure. Following the wildfire, building values drop sharply in the first post-event year (the largest decline in the figure),

then rebound partially. After this initial adjustment, the estimates remain negative for several years and gradually move back toward zero, ending the event window still slightly below baseline. The horizontal red line summarizes the average post-disaster effect over the post-event periods shown.

Panels B–F report the same event-study estimates separately by quintile of pre-disaster unit parcel value. The first quintile (Panel B) exhibits the largest and most volatile response. The initial post-event estimate drops sharply, with very wide confidence intervals, followed by a partial rebound; however, point estimates remain substantially below zero throughout most of the post-event window. The second quintile (Panel C) also experiences a pronounced immediate decline, though smaller than in the first quintile. Estimates then recover steadily over time, trending upward and approaching zero toward the end of the event window. The third quintile (Panel D) displays a more muted response. After a modest decline in the early post-event years, the coefficients remain slightly negative and relatively stable, with narrower confidence intervals than in the lower quintiles. In contrast, the fourth and fifth quintiles (Panels E and F) show little systematic response to wildfire exposure. Across these higher-value groups, post-event estimates remain close to zero throughout the event window, indicating limited average changes in assessed building values following wildfire exposure.

The figure indicates strong heterogeneity in post-wildfire building-value dynamics across the pre-disaster value distribution. Lower-value parcels experience much larger short-run losses and more persistent negative effects, whereas higher-value parcels exhibit substantially smaller responses, with the top quintile showing little systematic change over the event window.

Land value

Figure 5 reports stacked event-study estimates of the effects of wildfires on the log of tax-assessed land market values, for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A presents the full-sample estimates. Following wildfire exposure, land values decline gradually rather than sharply. The decline deepens over several years after the event, reaching levels around 15–20 percent below baseline, and remains persistently negative throughout most of the post-event window. Although there is some attenuation toward the end of the horizon, land values do not return to pre-disaster levels within the observed period. The horizontal red line summarizes the average post-disaster effect over the post-event window.

Panels B–F show heterogeneity across the pre-disaster value distribution. In the first and second quintiles (Panels B and C), land values decline following wildfire exposure and remain below baseline for much of the post-event period. The declines are moderate in magnitude, with point estimates most negative in mid-to-late post-event years and some recovery thereafter, though estimates remain imprecise at longer horizons. In the third and fourth quintiles (Panels D and E), exhibit broadly similar adjustment patterns. Land values decrease gradually following wildfire exposure, with point estimates trending downward over time. However, confidence intervals are wide throughout much of the post-event window, and the estimates are generally not statistically distinguishable from zero. These patterns suggest slower and more uncertain land-value adjustment in mid-range productivity areas. The fifth quintile (Panel F) shows no systematic decline in land values after the event. Post-

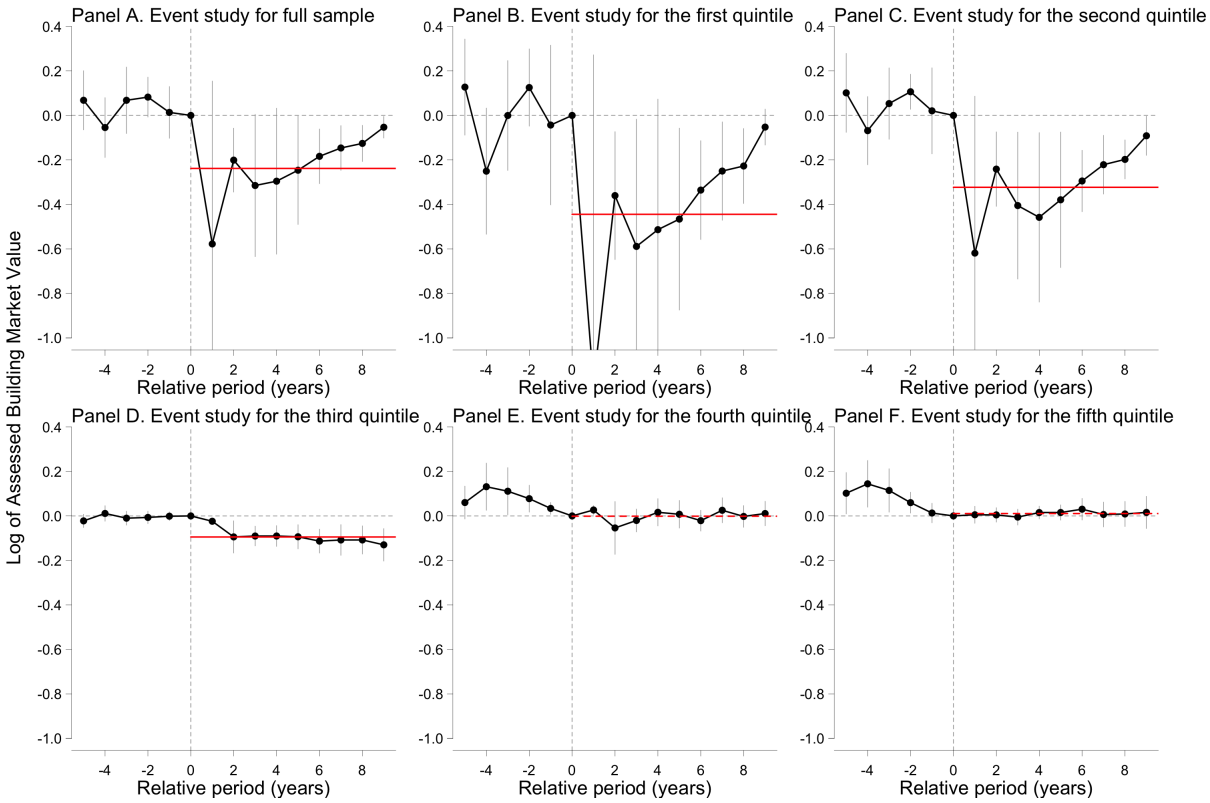


Figure 4: Treatment Effects of Wildfires on Assessed Building Values

Note: This figure presents estimates of wildfire treatment effects on tax-assessed building market values for parcels located within the burn perimeter, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A shows the event-study dynamic estimates for the full sample. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

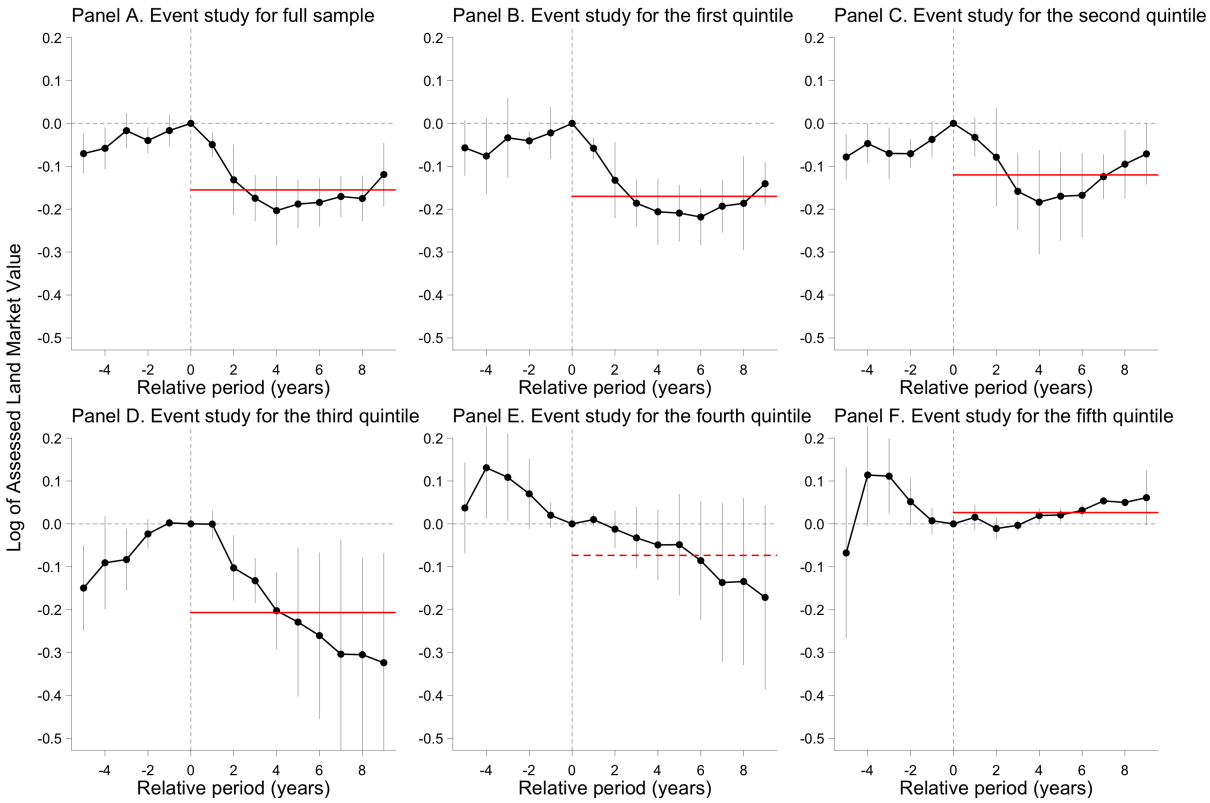


Figure 5: Treatment Effects of Wildfires on Assessed Land Values

Note: This figure presents estimates of wildfire treatment effects on tax-assessed land market values for parcels located within the burn perimeter, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A shows the event-study dynamic estimates for the full sample. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

disaster estimates remain close to zero initially and become mildly positive in later years, indicating relative resilience of land values in the highest-productivity locations.

The figure reveals substantial heterogeneity in land-value responses across the pre-disaster value distribution. Lower- and middle-value parcels experience persistent land-value losses following wildfire exposure, whereas higher-value parcels—particularly those in the top quintile—exhibit more resilient and, in some periods, positive land-value dynamics. Compared with building values, land values adjust more slowly and display more persistent post-disaster effects, underscoring distinct recovery mechanisms for land and structures.

Comparison between the top and bottom quintiles

While the quintile-specific event studies document pronounced heterogeneity in post-wildfire adjustment, visual comparisons alone do not establish whether differences between low- and high-productivity locations are statistically meaningful. To formally assess whether wild-

fire impacts differ across the extremes of the pre-disaster value distribution, we implement a Chow-type test comparing treatment effects for parcels in the first and fifth unit parcel value quintiles. The null hypothesis is that post-disaster dynamics are identical across the two groups, against the alternative that recovery paths differ systematically. This approach provides a direct test of differential adjustment and complements the quintile-specific analyses by quantifying whether observed gaps reflect statistically significant divergence rather than sampling variation.

Figure 6 plots the difference in stacked event-study coefficients between the top and bottom quintiles across event time. Panel A reports differences in total assessed market values. Pre-event coefficients are close to zero, indicating no evidence of differential pre-trends. After wildfire exposure, the estimated differences turn positive and remain so for most of the post-event window, implying that total values recover more strongly—or decline less—for high-productivity parcels relative to low-productivity parcels. The positive average post-disaster difference, shown by the horizontal red line, indicates a persistent gap in overall valuation responses between the two groups.

Panel B presents the corresponding differences for building values. The estimates show a sharp positive spike in the first post-event year, reflecting substantially larger immediate losses for low-productivity parcels following physical destruction. Although the magnitude of the difference declines over time, the post-event coefficients remain predominantly positive, and the average difference is positive, indicating stronger rebuilding and recovery of building values in high-productivity locations.

Panel C reports differences in land values. As in the other panels, pre-event coefficients are near zero. In the post-event period, the estimated differences are positive and relatively stable, suggesting that land values in high-productivity areas increase more, or decline less, than those in low-productivity areas following wildfire exposure. The positive average post-disaster difference indicates a sustained divergence in land-value adjustment between the two groups.

Overall, this figure provides formal statistical evidence that post-wildfire recovery differs systematically across the pre-disaster productivity distribution. High-productivity locations experience stronger recovery in total and building values and more favorable land-value adjustments relative to low-productivity locations. These results reinforce the central mechanism of the paper: wildfires act as a shock that amplifies pre-existing differences in local productivity, generating divergent recovery trajectories across space rather than uniform adjustment.

5.2 Spillover Effect

We next examine the spillover effects of wildfires on parcels located outside, but in close proximity to, the burn perimeter. In contrast to directly exposed parcels, these neighboring properties do not experience physical destruction. Instead, spillover effects may arise through neighborhood externalities, local amenities, and expectations about future development. Our analysis focuses on parcels located within a 0–500 meter buffer outside the burn perimeter, where spillover effects are most likely to be present. [4]As in the analysis of direct effects,

[4]The 500-meter boundary is not chosen arbitrarily. We estimate spillover effects using a series of distance bands in 100-meter increments outside the burn perimeter. Spillover effects are detectable within the first

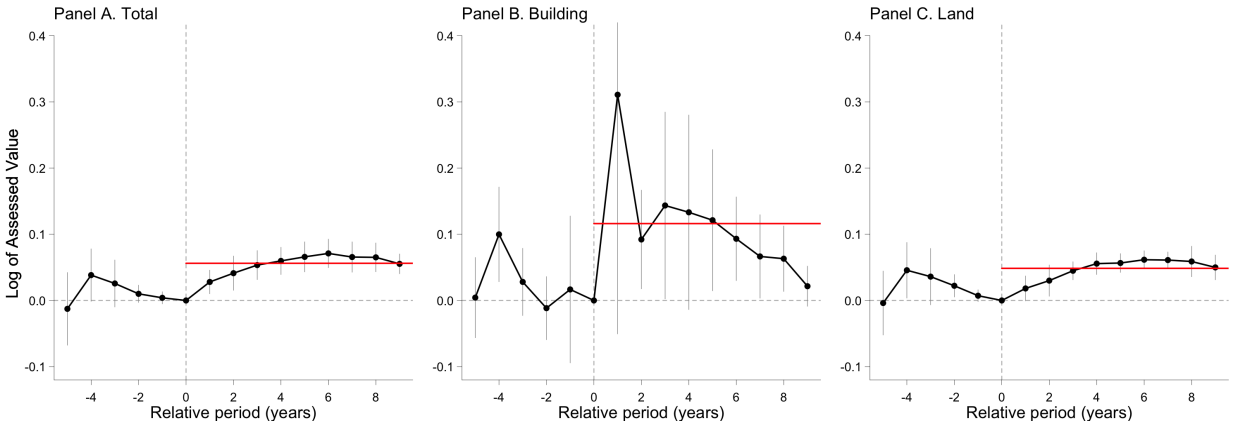


Figure 6: Differential effects between the lowest and highest pre-disaster value quintiles

we first present results for the full sample and then examine heterogeneity by pre-disaster parcel rank. Consistent with the theoretical framework, spillover responses may vary across locations depending on local productivity and how wildfire exposure alters expectations about future returns.

Total values

Figure 7 reports stacked event-study estimates of wildfire spillover effects on the log of total tax-assessed market values for parcels located within 0–500 meters outside the burn perimeter, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A presents the full-sample estimates. Pre-event coefficients are small and stable, providing no evidence of differential pre-trends. Following wildfire exposure in nearby areas, point estimates become mildly negative in the early post-event years but subsequently rebound toward zero. Throughout most of the post-event window, confidence intervals overlap zero, indicating that average spillover effects in the full sample are limited in magnitude and not statistically distinguishable from zero.

Panels B–F reveal substantial heterogeneity across the pre-disaster value distribution. In the lowest quintile (Panel B), spillover effects are negative in the post-event period, with several years exhibiting statistically significant declines in total assessed values relative to baseline. This pattern indicates that low-productivity neighborhoods experience adverse spillovers from nearby wildfire exposure. In contrast, the highest quintile (Panel F) displays positive post-event spillover effects: point estimates turn positive shortly after the event and remain above zero for several years, with confidence intervals that exclude zero in parts of the post-event window. This suggests that high-productivity areas benefit from nearby wildfire exposure, consistent with upgrading, reallocation, or amenity-driven responses in surrounding neighborhoods.

For the middle quintiles (Panels C–E), post-event coefficients are generally small and imprecisely estimated. Although point estimates vary in sign and magnitude over event

500 meters but become statistically indistinguishable from zero in the 500–600 meter band and beyond (see Figures S1-S3). Based on this pattern, we use parcels located 500–1000 meters from the burn perimeter as the never-treated control group in the spillover analysis.

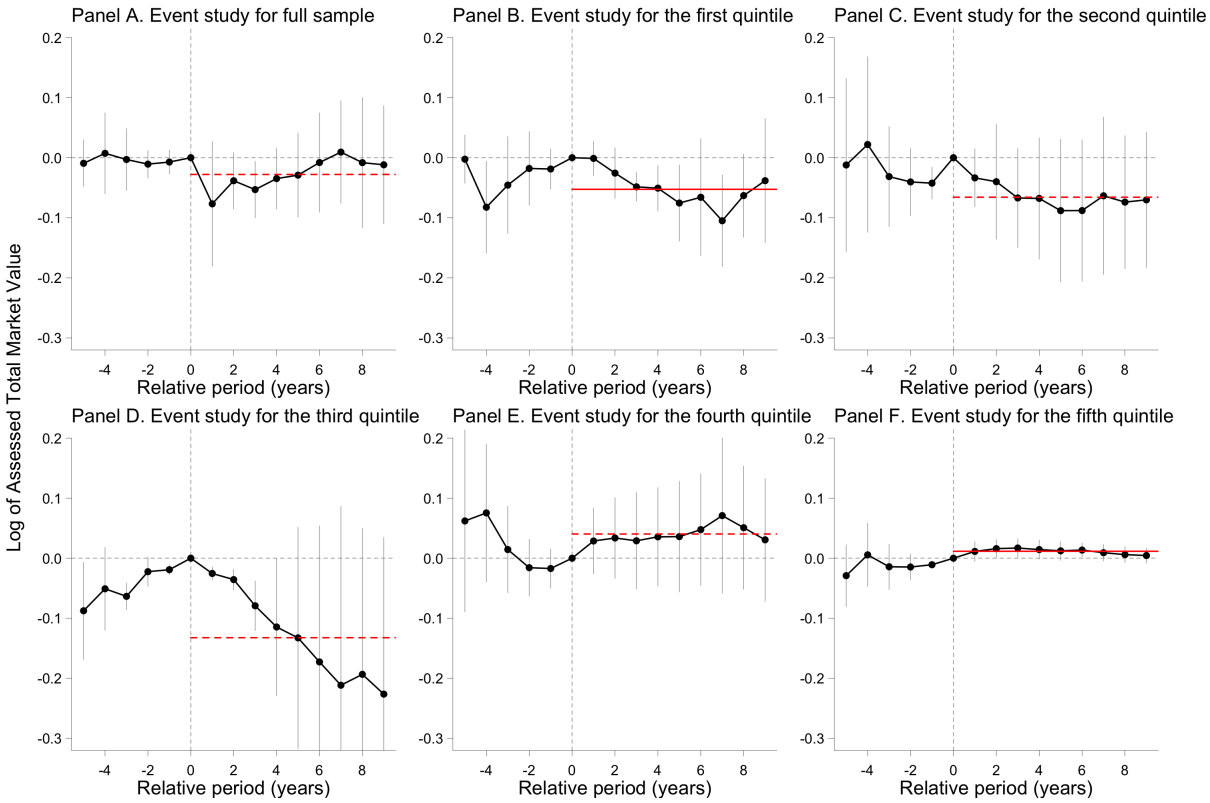


Figure 7: Spillover Effects of Wildfires on Total Assessed Values (500 m Buffer)

Note: This figure presents estimates of wildfire spillover effects on total tax-assessed market values for parcels located within a 500-meter buffer outside the burn perimeter, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A shows the event-study dynamic estimates for the full sample. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

time, confidence intervals largely overlap zero, indicating no robust spillover effects for these groups.

The figure shows that while average spillover effects of wildfires are modest in the aggregate, they mask pronounced heterogeneity across locations. Spillovers are negative in low-productivity areas and positive in high-productivity areas, consistent with the paper's central mechanism: local economic fundamentals shape not only on-site recovery but also the direction and magnitude of spatial spillovers to neighboring areas. These results reinforce the interpretation of wildfires as a form of spatially uneven creative destruction, amplifying pre-existing differences rather than equalizing outcomes across space.

Building value

Figure 8 reports stacked event-study estimates of wildfire spillover effects on the log of tax-assessed building market values for parcels located within 0–500 meters outside the burn

perimeter, for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A presents the full-sample estimates. Pre-event coefficients are stable and close to zero, indicating no evidence of differential pre-trends. Following wildfire exposure in nearby areas, point estimates fluctuate slightly around zero throughout the post-event period, and confidence intervals consistently include zero, implying no statistically meaningful spillover effects on building values at the aggregate level.

Panels B–F display the corresponding estimates by quintile. Across all quintiles, post-event coefficients remain small in magnitude and imprecisely estimated. While point estimates occasionally vary in sign over event time, none exhibit persistent or statistically significant departures from zero. This pattern holds for both lower- and higher-value parcels, indicating no systematic heterogeneity in building-value spillovers across the pre-disaster value distribution.

The results indicate that wildfire spillovers to nearby parcels do not materially affect building values. This finding is consistent with the underlying mechanism: buildings outside the burn perimeter do not experience direct physical damage, and reconstruction activity is concentrated within affected areas rather than in neighboring parcels. In contrast to land and total values—where spillovers reflect changes in neighborhood desirability and local economic fundamentals—building values in adjacent areas remain largely unchanged following wildfire exposure.

Land value

Figure 9 reports stacked event-study estimates of wildfire spillover effects on the log of tax-assessed land market values for parcels located within 0–500 meters outside the burn perimeter, for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A presents the full-sample estimates. In the pre-event period, coefficients are stable and close to zero, indicating no differential pre-trends. Following wildfire exposure in nearby areas, land values exhibit a small decline in the early post-event years, but the estimates rebound toward zero thereafter. Throughout most of the post-event window, confidence intervals include zero, suggesting that average land-value spillovers in the full sample are limited in magnitude and not precisely estimated.

Panels B–F reveal substantial heterogeneity across the pre-disaster value distribution. In the first quintile (Panel B), post-event land values decline and remain persistently negative over much of the event window, with several mid- to long-run estimates statistically distinguishable from zero. A similar but less pronounced pattern appears in the second quintile (Panel C), where point estimates are generally negative in the post-event period, though with wider confidence intervals. The third quintile (Panel D) shows a more gradual downward trajectory: land values drift increasingly negative over time, with later-period estimates becoming economically meaningful despite rising uncertainty.

In contrast, spillover effects differ markedly at the top of the distribution. In the fourth and fifth quintiles (Panel E and F), post-event estimates hover close to zero, with no clear evidence of sustained positive or negative spillovers. The fifth quintile (Panel F) displays a distinct pattern: land values increase modestly following wildfire exposure in neighboring areas, and post-event point estimates are consistently positive, with several periods indicating statistically meaningful gains.

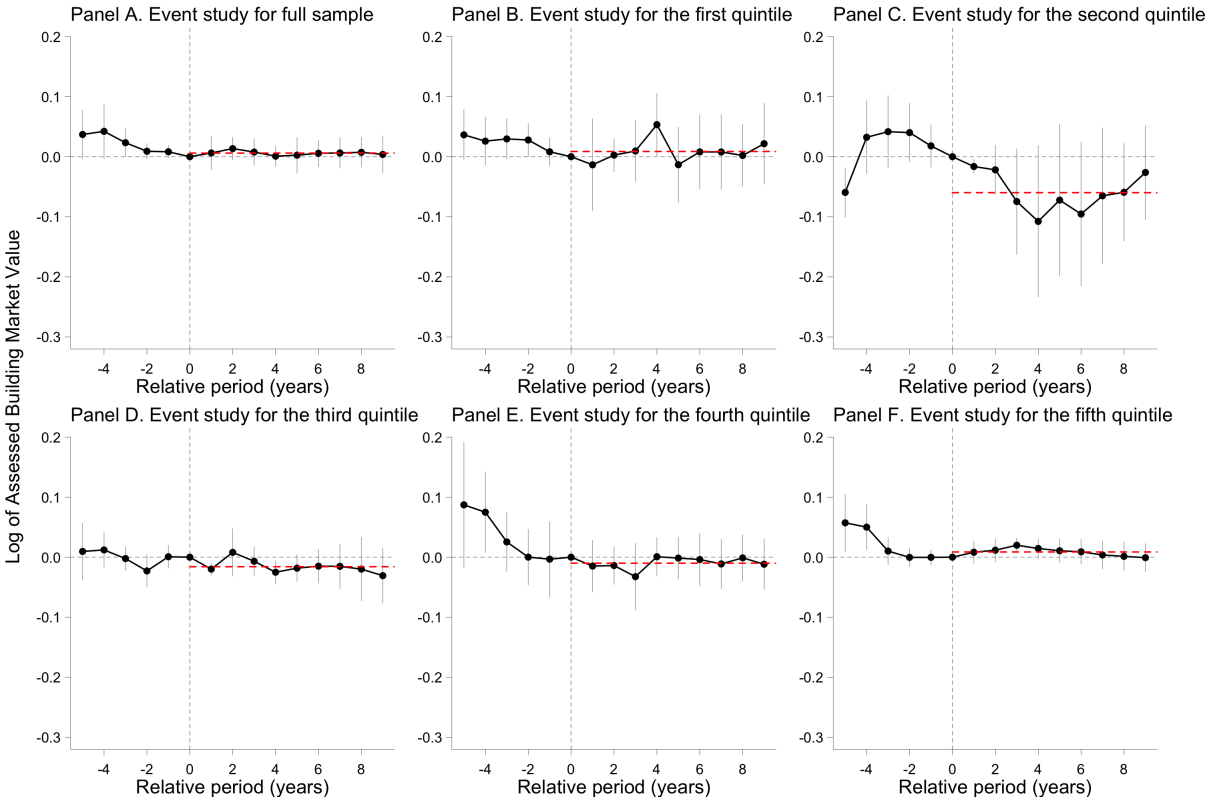


Figure 8: Spillover Effects of Wildfires on Assessed Building Values (500 m Buffer)

Note: This figure presents estimates of wildfire spillover effects on tax-assessed building market values for parcels located within a 500-meter buffer outside the burn perimeter, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A shows the event-study dynamic estimates for the full sample. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

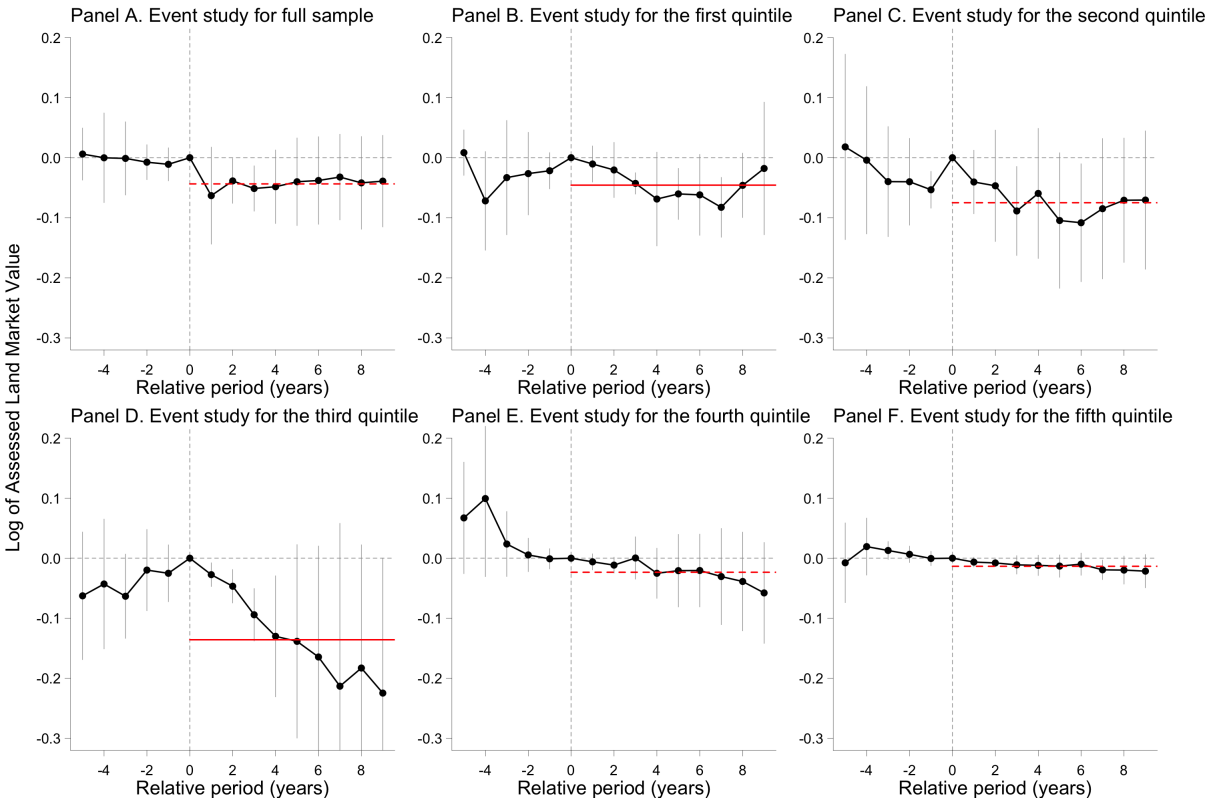


Figure 9: Spillover Effects of Wildfires on Assessed Land Values (500 m Buffer)

Note: This figure presents estimates of wildfire spillover effects on tax-assessed land market values for parcels located within a 500-meter buffer outside the burn perimeter, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A shows the event-study dynamic estimates for the full sample. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

In the next section, we test this mechanism directly by examining whether wildfire exposure leads to observable changes in housing characteristics.

6 Mechanism: Evidence of Changes in Housing Quality

The theory developed in Section 2 predicts that post-disaster recovery depends critically on local productivity. In high-productivity areas, households have strong incentives to rebuild destroyed structures at high quality, because upgraded housing yields higher future payoffs and is supported by complementary neighborhood investment. In contrast, in low-productivity areas, rebuilding incentives are weak, leading to delayed, partial, or low-quality reconstruction. These asymmetric rebuilding decisions generate divergence in housing and land values after disasters.

The previous section provides reduced-form evidence consistent with these predictions: building, land, and total property values recover and even rise in high-productivity areas, while remaining persistently depressed in low-productivity areas. However, these results alone do not establish how this divergence arises. In particular, higher post-disaster prices could in principle reflect changes in land fundamentals or compositional effects rather than active rebuilding and upgrading of the housing stock.

This section closes the mechanism by examining whether housing characteristics themselves change after wildfires, and whether these changes are consistent with rebuilding and quality upgrading. Because housing quality is not directly observed in the data, we focus on a set of assessor-recorded building attributes that are closely tied to construction decisions and are difficult to alter without substantial rebuilding.

6.1 Empirical Strategy

To test whether wildfires induce rebuilding and changes in housing quality, we re-estimate the baseline event-study specification using a set of housing characteristics as outcome variables. Rather than focusing on the levels of these characteristics, the analysis examines whether a given housing attribute changes following a wildfire.

Specifically, for each parcel i, housing characteristic k, and year t, the outcome variable is defined as an indicator equal to one if the recorded value of the characteristic differs from its value in the previous year, and zero otherwise:

$$Y_{i,t}^{k} = 1\left\{X_{i,t}^{k} \neq X_{i,t-1}^{k}\right\}$$

where $X_{i,t}^{k}$ denotes the value of housing characteristic k recorded by the tax assessor. This construction captures discrete changes in housing attributes which are unlikely to occur absent substantial reconstruction activity over time. Many housing characteristics in assessor data—such as year built, room counts, heating and cooling systems, roof materials, and foundation types—change infrequently and typically only when a structure is newly built or undergoes major renovation. As a result, a positive treatment effect reflects an increased probability that the housing stock is modified, rather than minor updates or valuation adjustments.

Using these outcomes, we estimate the same event-study specification as in the main analysis, including parcel fixed effects and county-by-year fixed effects. Identification comes from within-parcel changes relative to the not-yet-treated parcels. we estimate the model separately for parcels in different quintiles of pre-disaster unit parcel value, which serves as a proxy for local productivity and rebuilding incentives.

The estimated coefficients can be interpreted as the change in the probability that a given housing characteristic is altered in a given year following wildfire exposure. By focusing on whether housing attributes change at all, rather than on their levels, this strategy provides direct evidence on rebuilding activity and allows us to test the core mechanism of the model: that higher-productivity areas are more likely to rebuild and upgrade housing after disasters.

6.2 Evidence of Rebuilding and Quality Change

The results in Table 1 provide direct evidence that housing characteristics change after wildfires, consistent with active rebuilding rather than passive persistence of the pre-disaster housing stock.

First, the Year Built variable increases significantly after disasters across the sample and within each quintile. This pattern indicates that destroyed structures are replaced with newly constructed buildings rather than repaired in place. Because year built is only updated when a structure is newly constructed, this result directly confirms that rebuilding occurs following wildfire exposure.

Second, several interior structure measures change after disasters, including total rooms, bedrooms, and bathrooms. These changes indicate that rebuilt houses are not simple replicas of the original structures. Instead, rebuilding is accompanied by re-optimization of interior layouts and scale, consistent with households adjusting housing choices in response to updated incentives.

Third, the table documents systematic changes in structural and amenity-related attributes. Heating and cooling systems, parking or garage area, roof materials, foundation types, and exterior codes all exhibit statistically significant post-disaster changes for many groups. These characteristics are tightly linked to construction standards and building quality and are unlikely to change absent substantial reconstruction. Their movement therefore provides further evidence that post-disaster rebuilding involves meaningful upgrades to the physical housing stock.

Crucially, these changes are heterogeneous across pre-disaster unit parcel value quintiles. Higher-value areas exhibit more pronounced and consistent changes across multiple quality-related dimensions, while lower-value areas show fewer, smaller, or less systematic adjustments. This heterogeneity mirrors the divergence in post-disaster building and land values documented in Section 5.

Taken together, the results in Table 1 establish the missing link in the recovery mechanism. Wildfires induce rebuilding, but the quality of rebuilding varies systematically with pre-disaster local productivity. In high-productivity areas, rebuilding involves newer construction, altered layouts, and upgraded structural features, consistent with quality upgrading. In low-productivity areas, rebuilding is more limited, contributing to persistent declines in housing and land values. These findings validate the model's central mechanism: disasters act as a selection and re-optimization shock to the housing stock, amplifying pre-existing

productivity differences. The observed post-disaster divergence in property values is therefore not merely a price-level phenomenon, but reflects underlying changes in the physical quality of housing induced by heterogeneous rebuilding incentives.

Many of the characteristics studied—such as year built, foundation type, and roof material—are only updated when substantial reconstruction occurs and change infrequently in normal times. The sharp post-disaster increase in the probability of change for these variables is therefore unlikely to reflect routine reassessment.

Table 1: Estimated Treatment Effects on Housing Characteristics

	Total	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Year Built	0.0064***	0.0047**	0.0293***	0.0112***	0.0210***	0.0141***
	(0.0016)	(0.0016)	(0.0042)	(0.0019)	(0.0013)	(0.0000)
Rooms Count	0.0007	-0.0005	0.0033**	0.0028***	0.0260***	0.0360***
	(0.0005)	(0.0008)	(0.0015)	(0.0004)	(0.0012)	(0.0000)
Bedrooms Count	0.0034**	0.0011	0.0184***	-0.0088***	0.0155***	0.0216***
	(0.0012)	(0.0016)	(0.0020)	(0.0004)	(0.0015)	(0.0000)
Bath Count	0.0017	0.0057**	0.0257***	-0.0045***	0.0115***	-0.0002***
	(0.0011)	(0.0021)	(0.0047)	(0.0008)	(0.0019)	(0.0000)
Cooling	0.0112***	-0.0023	0.0192***	-0.0227***	-0.0234***	-0.0049***
	(0.0026)	(0.0066)	(0.0011)	(0.0000)	(0.0000)	(0.0000)
Heating	0.0085***	0.0235*	-0.0066**	0.0260**	0.0318***	0.0054***
	(0.0027)	(0.0131)	(0.0028)	(0.0094)	(0.0000)	(0.0000)
Parking Garage Area	0.0019	0.0015	0.0292***	0.0071***	0.0217***	0.0180***
	(0.0012)	(0.0013)	(0.0050)	(0.0010)	(0.0015)	(0.0000)
Roof Material	-0.0101**	0.0113	0.0104***	0.0000	0.0165***	
	(0.0039)	(0.0081)	(0.0029)	(0.0000)	(0.0000)	
Foundation	-0.0056	0.0083**	0.0014			
	(0.0046)	(0.0033)	(0.0009)			
Exterior Code	0.0061***	-0.0122**	-0.0054			
	(0.0021)	(0.0043)	(0.0037)			

Note: This table reports estimated treatment effects of wildfire exposure on housing characteristics, using a stacked event-study difference-in-differences specification. Columns report estimates for the full sample and separately by pre-disaster unit parcel value quintiles. Each coefficient captures the average post-disaster change relative to the pre-event baseline. Standard errors are clustered at the wildfire-event level and reported in parentheses.
Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

7 Conclusion

This paper investigates why some communities rebound after disasters while others stagnate or decline. We develop a general equilibrium model of urban growth that highlights the role of spillover effects in reconstruction decisions. Disasters synchronize rebuilding across many landowners, forcing them to internalize cross-building externalities that are typically ignored in normal times. Whether this coordination accelerates or dampens recovery depends critically on pre-disaster local economic conditions, which shape expectations about the value of reinvestment. Our empirical analysis, leveraging more than 1,000 wildfires linked to parcel-level tax assessments, provides clear support for this mechanism: similar shocks

produce sharply divergent recovery trajectories depending on the affected area's baseline productivity.

Our results show that, on average, wildfires reduce long-run property values. However, this average masks strong heterogeneity. Properties in low-value areas suffer persistent declines, those in middle-value areas recover to baseline levels, and those in high-value areas experience sustained gains—consistent with a process of "creative destruction." Importantly, these dynamics extend beyond the burn perimeter. Unburned parcels in the vicinity mirror the positive or negative trajectories of their burned neighbors, revealing that spillovers are central to shaping recovery. These findings underscore that disasters do not operate in isolation on individual parcels but instead reshape entire neighborhoods through simultaneous rebuilding decisions.

Beyond documenting divergent price trajectories, this paper provides direct evidence on the underlying mechanism driving recovery. By examining changes in assessor-recorded housing characteristics, we show that wildfires induce active rebuilding rather than simple persistence of the pre-disaster housing stock. Crucially, the extent and nature of rebuilding vary systematically with pre-disaster local productivity. High-productivity areas experience more frequent reconstruction, newer construction vintages, and meaningful changes in structural features and amenities, consistent with quality upgrading. In contrast, rebuilding in lower-productivity areas is more limited, helping to explain their persistent declines in land and building values. These findings confirm that post-disaster divergence reflects real changes in the physical housing stock, not merely price revaluation.

Together, these results show that identical disaster shocks can produce sharply divergent recovery paths across space, driven by differences in rebuilding incentives, housing quality adjustment, and spillover effects. In this sense, disasters function as a form of spatially uneven destruction, amplifying pre-existing differences rather than equalizing them.

The policy implications are substantial. Because private incentives alone are insufficient to capture neighborhood spillovers, disaster recovery outcomes hinge on whether positive or negative externalities dominate. In weaker economies, disasters risk locking neighborhoods into decline, while in stronger economies, they can catalyze renewal. This suggests a critical role for policy in coordinating rebuilding efforts, lowering barriers to reinvestment, and designing subsidies or zoning rules that promote higher-quality reconstruction. More broadly, recovery policies should aim to replicate the beneficial aspects of disaster-induced rebuilding—simultaneity and positive spillovers—without imposing the social and economic costs of destruction itself.

One potential concern is whether differences in housing insurance coverage or disaster assistance could account for the heterogeneous rebuilding patterns documented in this paper. While insurance and government aid undoubtedly play an important role in post-disaster recovery, they are unlikely to explain the systematic divergence observed here. In the U.S. context, insurance coverage for owner-occupied housing is widespread, and lower-income areas often receive a relatively higher share of reconstruction funding through a combination of insurance payouts and public disaster assistance. By contrast, in higher-value areas, insurance limits and government transfers typically cover a smaller fraction of the cost required to rebuild housing to its pre-disaster standard or to upgrade quality. As a result, differences in insurance coverage alone would predict the opposite pattern of recovery from what the data reveal. This suggests that the heterogeneous rebuilding outcomes documented in this

paper are more plausibly driven by differences in rebuilding incentives and local economic fundamentals, rather than by variation in insurance coverage or disaster aid.

Several other limitations of our study point to fruitful directions for future research. First, while we document heterogeneous recovery trajectories across property value quintiles, we abstract from distributional outcomes within households—for example, who bears the costs of decline or who captures the gains from creative destruction. Linking parcel-level outcomes to household income or demographic characteristics would shed light on the equity implications of disaster recovery. Second, our analysis focuses on property values as the primary measure of recovery, but disasters may also reshape local labor markets, fiscal capacity, and migration patterns, which merit further exploration. Finally, while wildfires provide a rich and frequent natural experiment, extending the analysis to other types of disasters—such as floods, hurricanes, or earthquakes—would help assess the generalizability of our findings and deepen understanding of how different forms of destruction interact with local economic fundamentals.

Taken together, our findings highlight that disasters are pivotal moments in the life cycle of neighborhoods. By compelling simultaneous rebuilding, they can either exacerbate decline or unlock growth, depending on local conditions and expectations. The challenge for researchers and policymakers is to understand and harness these dynamics: to anticipate where disasters are likely to entrench vulnerabilities, and to design policies that channel rebuilding into pathways of resilience and long-run prosperity.

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Appendix

A1 Proofs

Proof of Lemma 1 By definition of $\underline{q}$:

$$r(\underline{q},\ Q,\ A) + \beta\left(dV(0,\ Q,\ A) + (1-d)V(\underline{q},\ Q,\ A)\right) = r(q^*,\ Q,\ A) + \beta\left(dV(0,\ Q,\ A) + (1-d)V(q^*,\ Q,\ A)\right) - c(q^*),$$

which can be simplified as

$$r(\underline{q},\ Q,\ A) + \beta(1-d)V(\underline{q},\ Q,\ A) = r(q^*,\ Q,\ A) + \beta(1-d)V(q^*,\ Q,\ A) - c(q^*).$$

Since both $r(q,\ Q,\ A)$ and $V(q,\ Q,\ A)$ are increasing in q, q^* needs to be larger than $\underline{q}$ given that $c(q^*) > 0$.

To see how q^* change with A and Q, the F.O.C. of

$$\max_q\ r(q,\ Q,\ A) + \beta\left(dV(0,\ Q,\ A) + (1-d)V(q,\ Q,\ A)\right) - c(q)$$

is

$$\frac{\partial r}{\partial q} + \beta(1-d)\frac{\partial V}{\partial q} - c'(q) = 0.$$

By the Implicit Function Theorem:

$$\frac{dq^*}{dA} = -\frac{\frac{\partial^2 r}{\partial q \partial A}}{\frac{\partial^2 r}{\partial q^2} + \beta(1-d)\frac{\partial^2 V}{\partial q^2} - c''(q)}.$$

As the denominator is smaller than zero and $\frac{\partial^2 r}{\partial q \partial A} = \frac{\partial^2 H}{\partial q \partial a}\tau a'(T) > 0$, $\frac{dq^*}{dA} > 0$. Similarly we can get $\frac{dq^*}{dQ} > 0$. □

Proof of Lemma 2 We prove the case of $Q^B < q^*$. $q^{*,post}$ cannot be lower than q^*. To see this, $q^{*,post}/\bar{q}_B$ of burned properties will be rebuilt to $q^{*,post}$. As $\{q\}_B$ uniformly ranges from $\underline{q}$, we will have a higher average quality of these burned properties: $Q_B^{post} > Q_B$, hence higher average quality for the whole region, i.e., $Q^{post} > Q$. By Lemma 1, $q^{*,post} > q^*$. As $V(0, Q, A)$ is increasing in Q, we have $V(0,\ Q^{post},\ A) > (<) V(0,\ Q,\ A)$. □

Proof of Proposition 1 It follows Lemma 1 and 2: if $A > \bar{A}$, $q^* > Q^B$. Otherwise, $q^* \leq Q^B$. □

A2 Identify the spatial extent of spillover effects

To determine the spatial boundary over which wildfire spillover effects are detectable, we estimate stacked event-study specifications using a sequence of increasingly distant buffer bands outside the burn perimeter. The results indicate that spillover effects are present

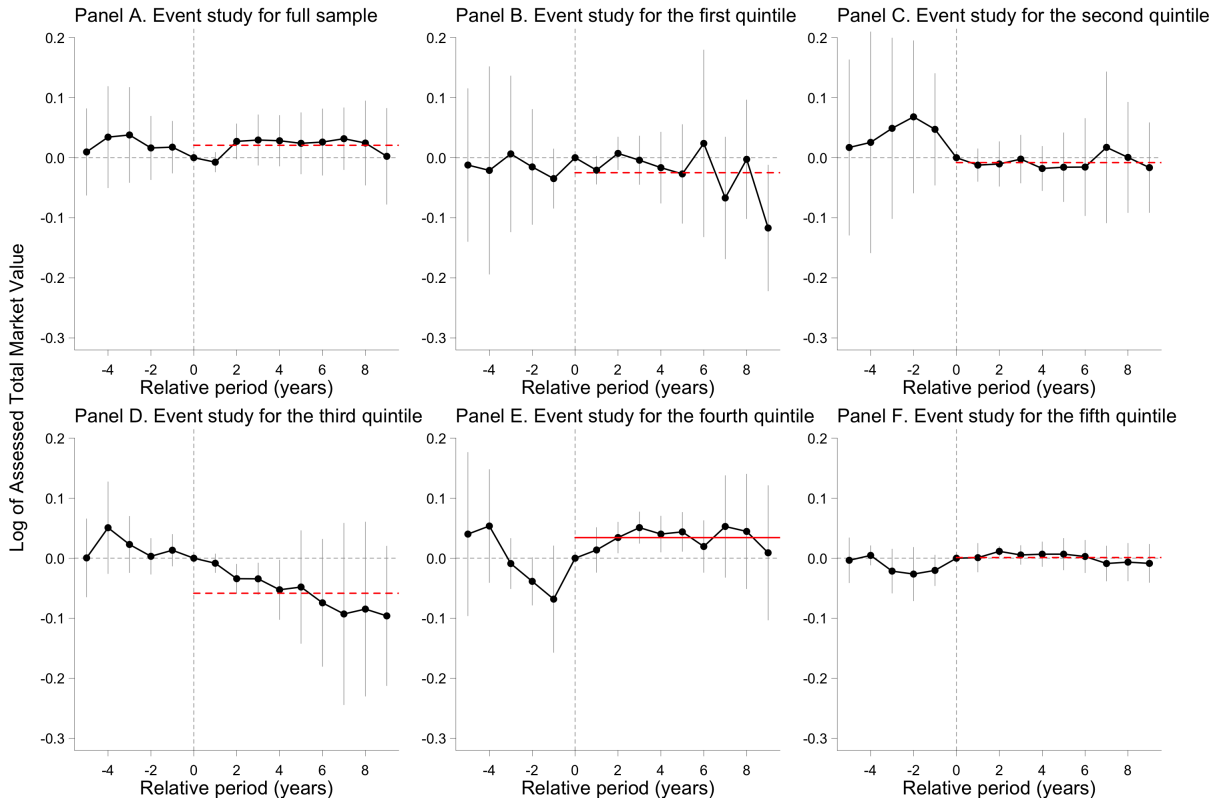


Figure S1: Spillover Effects of Wildfires on Total Assessed Values (500–600 m Buffer)

Note: This figure presents estimates of wildfire spillover effects on total tax-assessed market values for parcels located within a 500–600 meter buffer outside the burn perimeter, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A shows the event-study dynamic estimates for the full sample. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

within the first 500 meters but become statistically indistinguishable from zero in the 500–600 meter band and beyond (see Figures [fig:sse-total]–[fig:sse-land]). Consistent with this pattern, we treat parcels located 500–1000 meters from the burn perimeter as never-treated observations in the spillover analysis. This choice ensures that the control group lies outside the range where wildfire spillovers are empirically detectable, while remaining geographically close and comparable to treated parcels.

A3 Robustness Check

A3.1 Excluding Early Sample Years

Our baseline specifications use a five-year pre-treatment window to assess pre-trends. Because the assessment data begin in 2007—just prior to the Global Financial Crisis—these

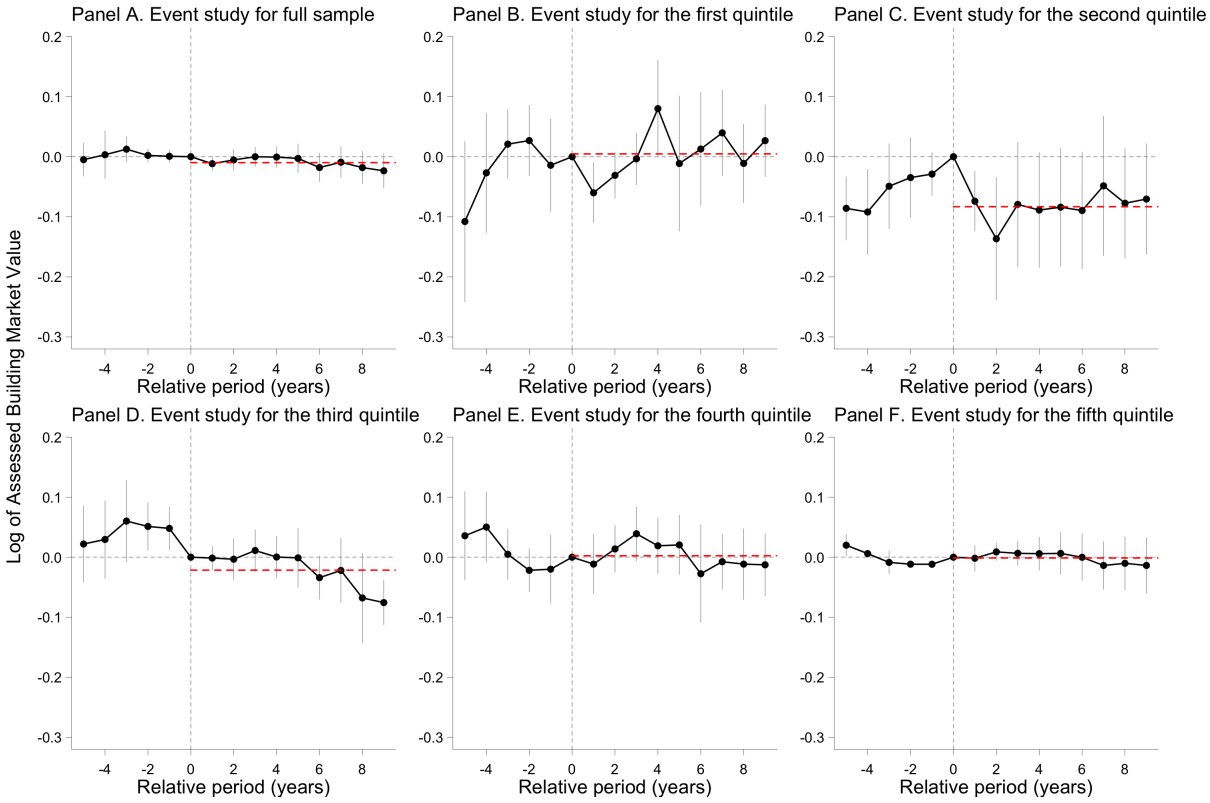


Figure S2: Spillover Effects of Wildfires on Assessed Building Values (500–600 m Buffer)

Note: This figure presents estimates of wildfire spillover effects on tax-assessed building market values for parcels located within a 500–600 meter buffer outside the burn perimeter, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A shows the event-study dynamic estimates for the full sample. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

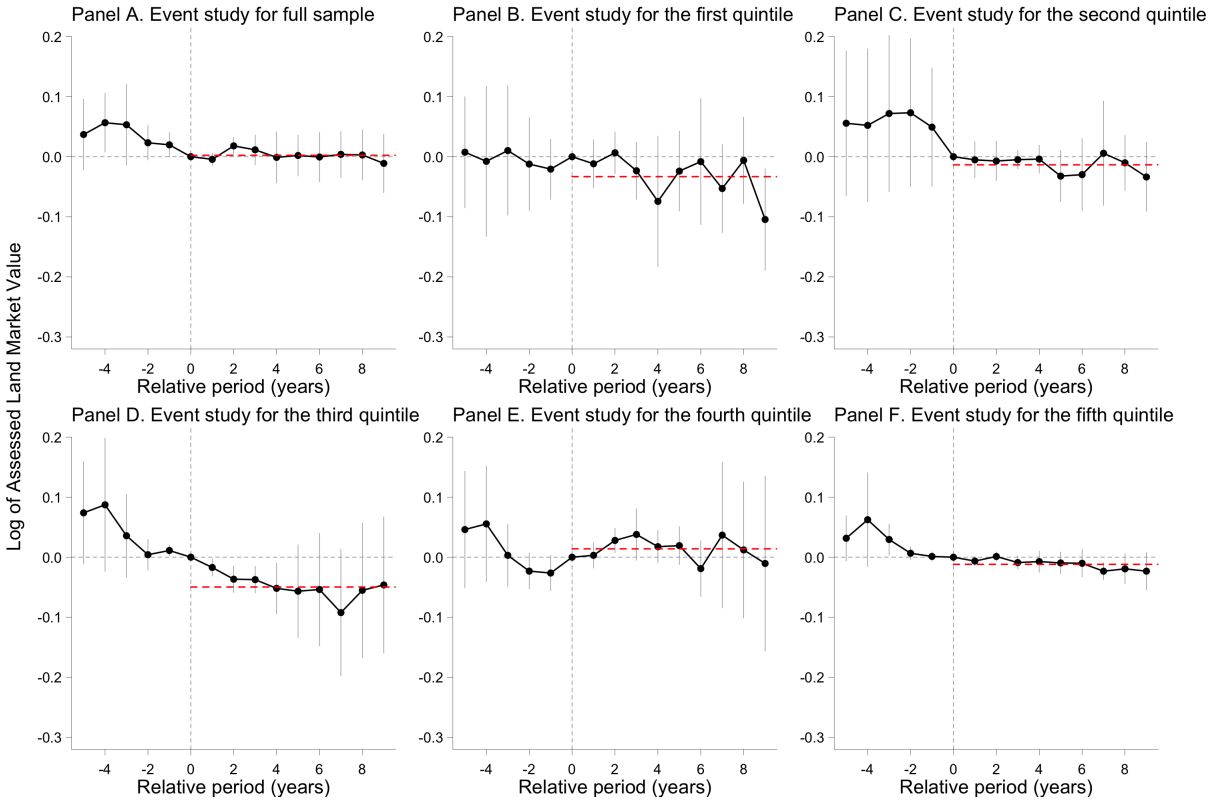


Figure S3: Spillover Effects of Wildfires on Assessed Land Values (500–600 m Buffer)

Note: This figure presents estimates of wildfire spillover effects on tax-assessed land market values for parcels located within a 500–600 meter buffer outside the burn perimeter, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panel A shows the event-study dynamic estimates for the full sample. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

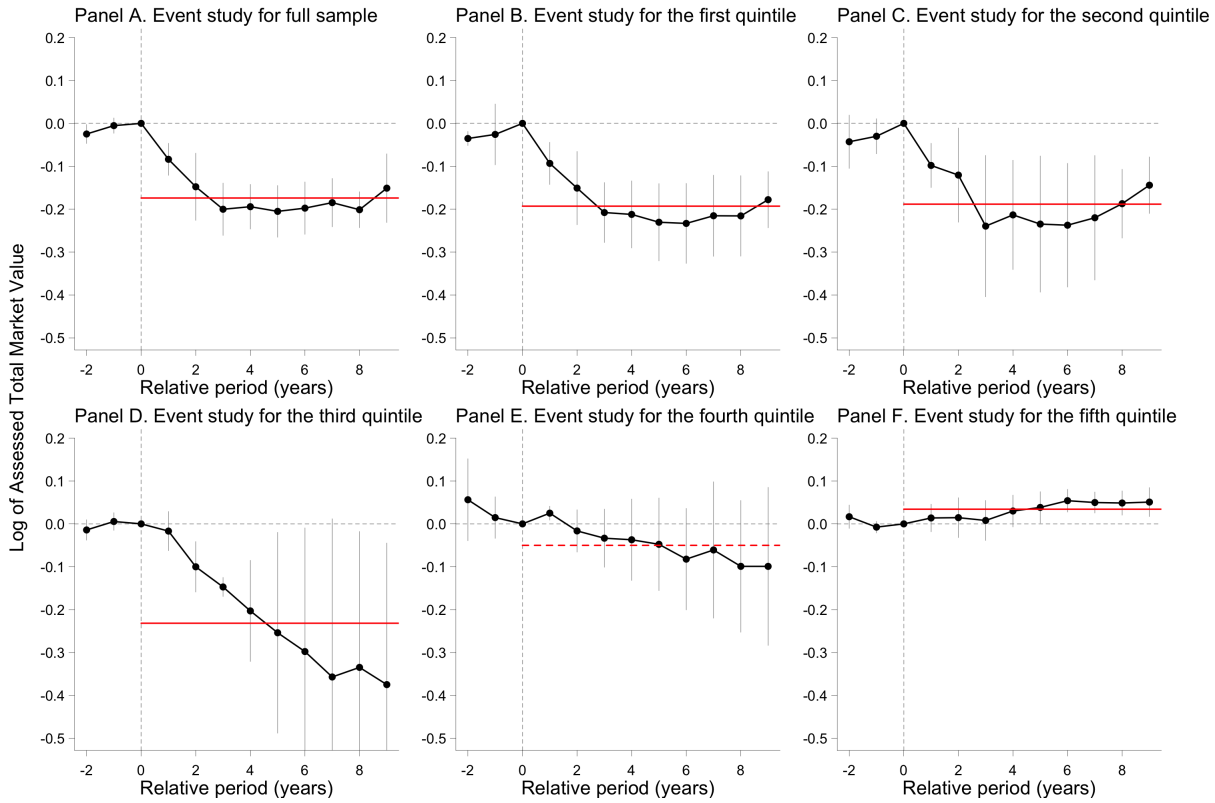


Figure S4: Treatment Effects of Wildfires on Total Assessed Values (Excluding 2007–2009)

Note: This figure presents estimates of wildfire treatment effects on total tax-assessed market values based on the post-2009 sample, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

early years may reflect atypical housing market conditions. Although observations from 2007–2009 enter only as pre-treatment periods and therefore do not directly affect estimated post-treatment dynamics, we examine the sensitivity of our results to excluding them. As a robustness check, we re-estimate all baseline treatment and spillover specifications starting in 2010, which leaves two pre-treatment years. The resulting event-study patterns and estimated magnitudes remain qualitatively similar to the baseline results.

A4 Supplementary Figures and Tables

A4.1 Data

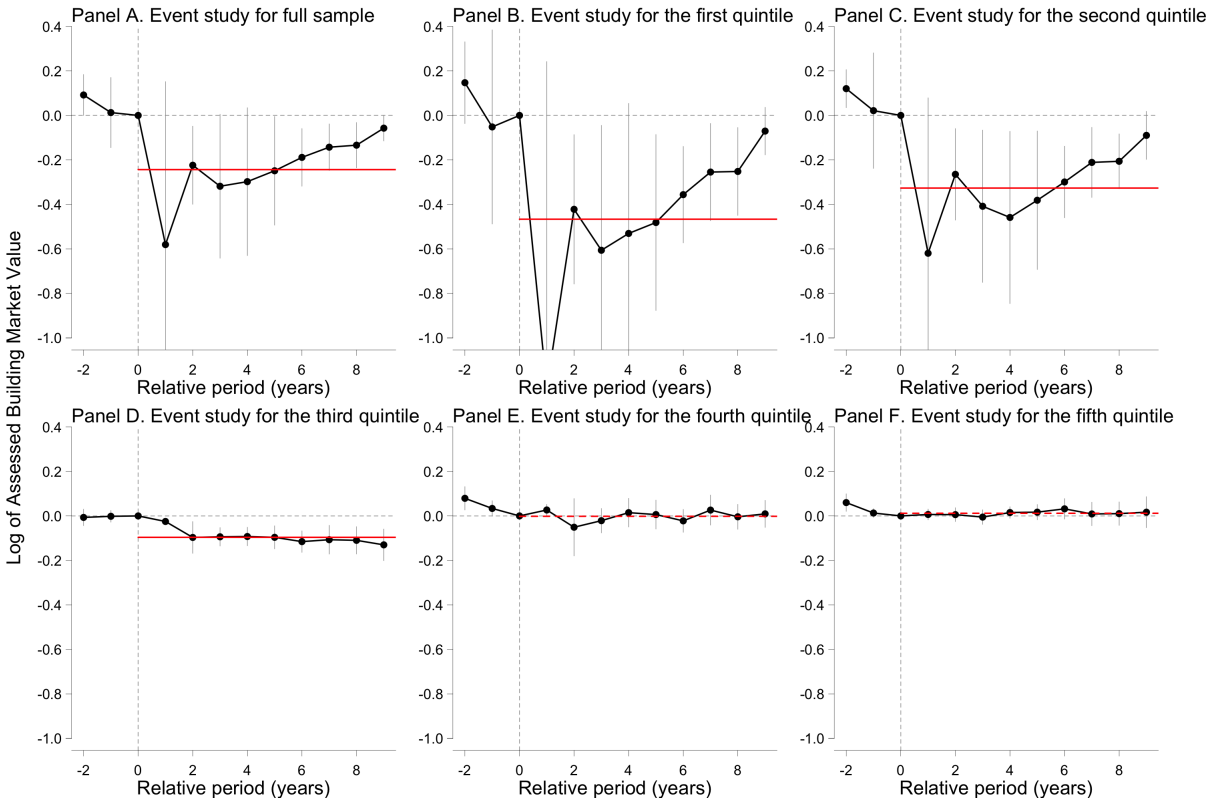


Figure S5: Treatment Effects of Wildfires on Assessed Building Values (Excluding 2007–2009)

Note: This figure presents estimates of wildfire treatment effects on tax-assessed building market values based on the post-2009 sample, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

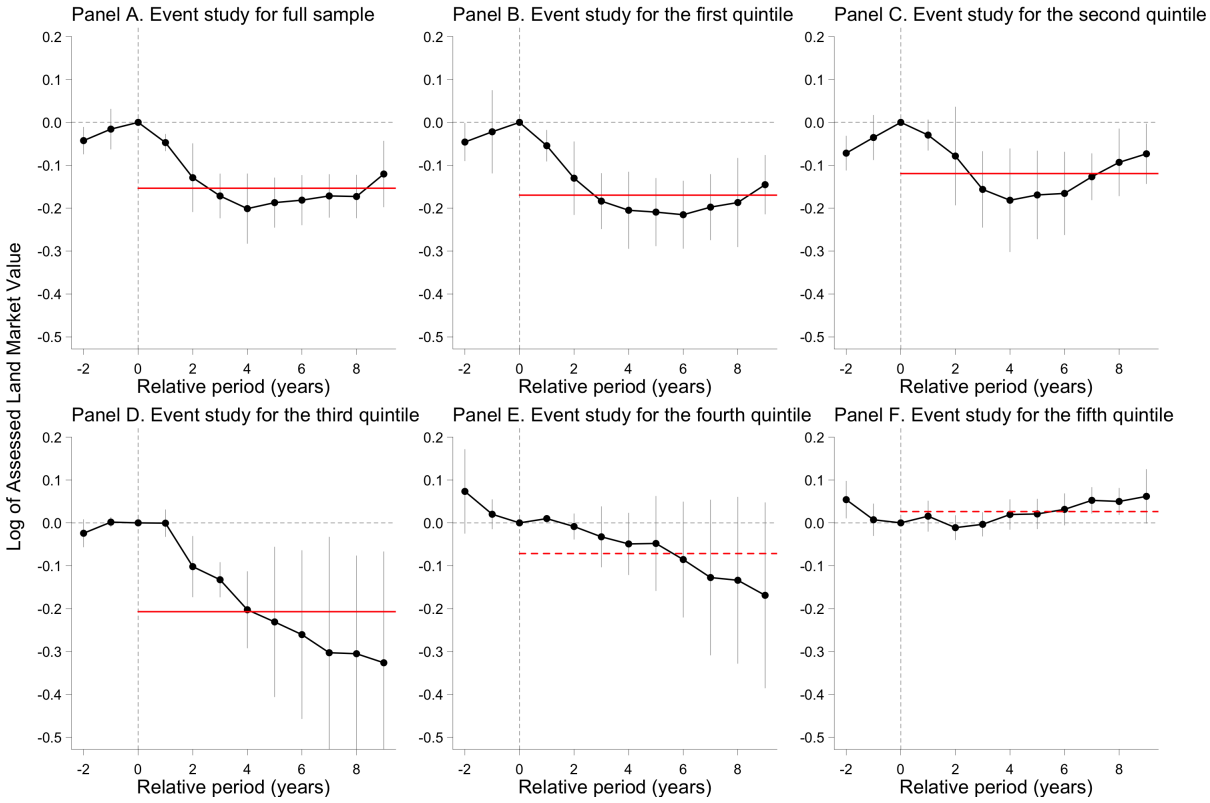


Figure S6: Treatment Effects of Wildfires on Assessed Land Values (Excluding 2007–2009)

Note: This figure presents estimates of wildfire treatment effects on tax-assessed land market values based on the post-2009 sample, shown for the full sample and separately by pre-disaster unit parcel value quintiles. Panels B–F report the same event-study specification estimated separately for parcels in the first through fifth quintiles of pre-disaster unit parcel value (ranked within state). Each point is the estimated coefficient for the year relative to the event time, and vertical bars denote 95% confidence intervals. The vertical dashed line marks the event year, and the horizontal dashed line indicates zero effect. The red lines denote the average post-disaster effect across all years, with a solid line indicating statistical significance at the 95% level.

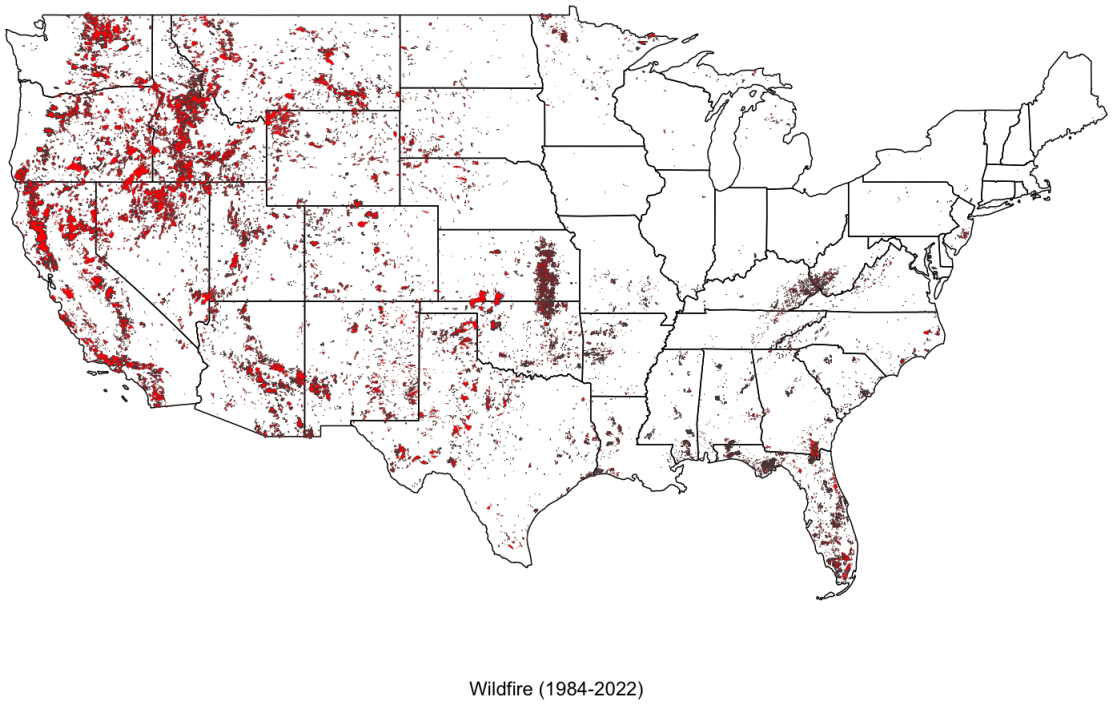


Figure S7: Map of Wildfires (1984-2022)

Note: This figure shows the geographic distribution of wildfires in the United States during the period 1984–2022.